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Using neural networks to examine trending keywords in Inventory Control

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Abstract
Inventory control is one of the key areas of research in logistics. Using the SCOPUS database, we have processed 9,829 articles on inventory control using triangulation of statistical methods and machine learning. We have proven the usefulness of the proposed statistical method and Graph Attention Network (GAT) architecture for determining trend-setting keywords in inventory control research. We have demonstrated the changes in the research conducted between 1950 and 2021 by presenting the evolution of keywords in articles. A novelty of our research is the applied approach to bibliometric analysis using unsupervised deep learning. It allows to identify the keywords that determined the high citation rate of the article. The theoretical framework for the intellectual structure of research proposed in the studies on inventory control is general and can be applied to any area of knowledge.

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1. Introduction

The rapidly growing knowledge base in the area of logistics and supply chain management (SCM) leads to challenges in determining the direction of ongoing changes in research and development of scientific pathways (Durach, Wieland, & Machuca, 2015; Richey & Davis-Sramek, 2020). Inventory control is a key challenge for logistics with a long history of research and multiple analytical approaches (Costantino, Di Gravio, Shaban, & Tronci, 2014; Woo, Moon, & Kim, 2021). When focusing on all logistics problems, inventory management is a real reflection of the signs of improper management of physical flows. Inventory is the lens through which imperfections in decision-making processes at all levels of the supply chain are visible. Understanding the achievements and intellectual structure of inventory management has been the subject of previous research using bibliometric methods and systematic literature reviews (Elmaghraby and Keskinocak, 2003; Gallino et al., 2017; Gardner, 1985; Gardner, 2006; Gordon et al., 2002; Guide and Srivastava, 1997; Soman et al., 2004). However, the specificity of supply chain management requires the adaptation of bibliometric analysis to this area of knowledge. Durach et al., (2017) who have examined the set of 133 Systematic Literature Reviews (SLRs) accurately note that despite numerous bibliometric analyses conducted, only 4 of them have been published in the top 30 journals ranked in the Thomson Reuters Journal Citation Report (Ranking 2015 | Management). Available scientific publications in databases such as SCOPUS, Web of Science (Social Science Citation Index), Lens, ABI-Inform/ProQuest and Science Direct are characterised by great diversity due to the type of publication e.g., article, book, review etc. and a huge number of documents.

In bibliometric research, such programs as VosViewer, Gephi, Pajek, Citnetexplorer, Bibexcel, Bibliometrix R, HistCite, Sci Mat or Sci2 are commonly used allowing researchers to track the growth of knowledge in a given field.

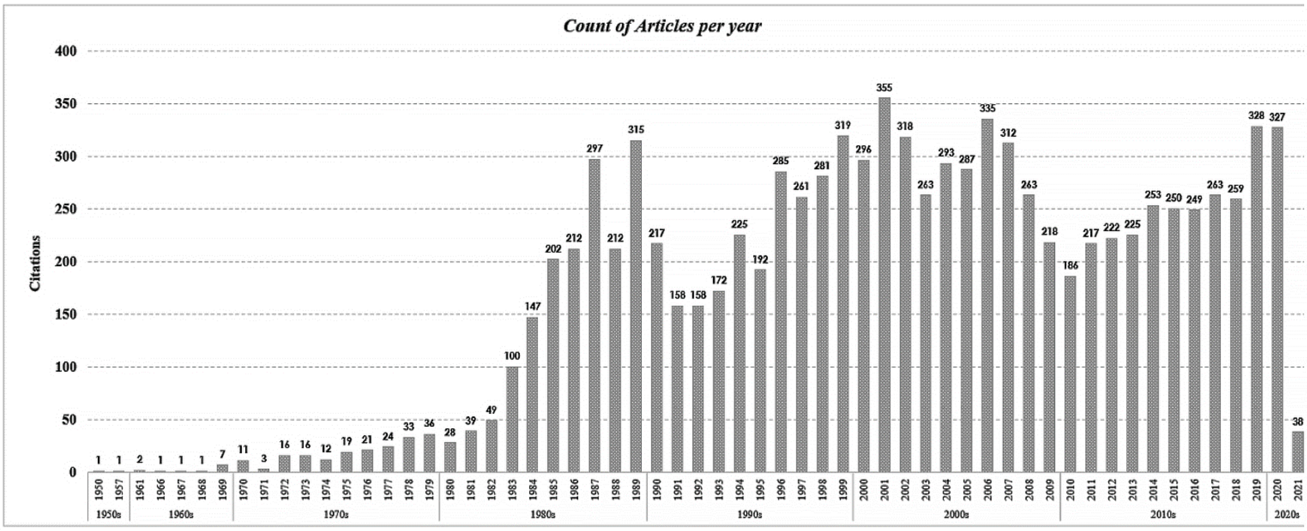

Fig. 1. Number of articles on inventory control

This approach is widely accepted by the scientific community and gives the possibility for a research process replication, which is important from the point of view of the reliability of the obtained research results. Existing methodological approaches to carrying out bibliometric analysis are also characterised by the fact that the research process is divided into stages (Donthu et al., 2021). Commonly used software allows scientists to visualise the network of links connecting authors, documents and keywords.

In our research, unlike in previous bibliometric studies, we have used a neural network to process a set of articles from the area of inventory control. A 2-layer network was built to solve the issue of indicating the most important keywords that describe research areas. The novelty of our research is the use of the graph attention network (GAT) to determine the list of keywords that have shaped inventory control research over decades. In our research, we have used articles from the SCOPUS database which is one of the largest bibliometric databases used in determining the intellectual structure. To identify the keywords that had the greatest impact on the development of inventory control, we have used a database of 10,190 articles for the query TITLE-ABS-KEY (“inventory control”) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (SUBJAREA, “ENGI”) OR LIMIT-TO (SUBJAREA, “BUSI”)) AND (LIMIT-TO (LANGUAGE, “English”)), downloaded on February 16, 2021. We have not only shown which words shape research in the area of inventory control, but also what impact a given word has on future citations of the article.

A contribution to the methodology of bibliometric research is the proposed new multi-stage research scheme including statistical analysis of a set of articles in terms of defining the keywords that indicate the areas of research conducted in a given field. This stage was carried out using statistical methods implemented in the Python environment on a database containing articles from the IC area exported from the SCOPUS database. In the second stage, we used the GAT to determine the keywords that best describe the directions of research over the decades in the period from 1950 to 2021.

Based on statistical analysis, we have formulated the first research question:

1. *What keywords were found in the largest cumulative number of citations?*

The second and third questions are based on the machine learning approach and neural networks:

1. *What are the keywords that mark the areas of inventory control research across decades?*
2. *Which words influence the high number of citations of articles in the field of inventory control?*

Inventory control is a fundamental area in logistics. Considering the massive number of papers, it is difficult to scrutinise all the links between trending papers to reveal the impact of keywords on publishing trends. Available software has some limitations and we have managed to overcome those thanks to machine learning and neural network approach. The publishing trend in inventory control is undergoing a slight decline (Fig.1) leading to a real problem with accuracy/blurring in trending.

Machine learning and deep learning methods yield great results in modelling complex datasets. These algorithms build a mathematical model from sample data for forecasting or decision-making, called a learning set. Importantly, the researcher is only required to define the problem, whereas the way of solving it is determined through the learning process conducted by the algorithm. Through iterative optimization, these methods uncover underlying patterns and relationships within the data that can be leveraged for predictive analytics or insightful decision-making. This automation of problem-solving not only accelerates the discovery process but also often unveils solutions that may not be intuitive to a human investigator, thereby pushing the boundaries of what can be achieved in data-driven research and applications.

2. Complexity of Inventory Control

Inventory control as part of logistics and it is basis for a number of conceptual models to analyse and guide operations, such as single and multi-stage lot-sizing models, multi-location news-vendor models, closed-loop inventory renting models (Raviv and Kolka, 2013), economic order quantity models (EPQ/EOQ) (also with carbon emission factors (Hua et al., 2011a) for sustainable EOQ (Battini et al., 2014) and for perishable products (Hiassat et al., 2017), multi-period stochastic inventory models, and supply chain coordination and contracting models. Inventory management is about building the right inventory – performance relationship.

Inventory control was part of the operational strategy in the 1980s where the focus was on vertical integration of processes around strategy, while in the 1990s the focus was on horizontal process integration (Frohlich and Westbrook, 2001). The most well-known model of inventory control is the Economic Production Quantity/Economic Order Quantity Inventory Control. It is commonly used in inventory control. At the same time, it is limited primarily by the assumption that manufactured products will be of perfect quality. In 2000s the focus was, among others, on research on imperfect product quality. From 2010-2020, the focus has mainly been marked by growing opportunities to minimise the error of demand forecasts, reduce the unpredictability of large orders (order smoothing, replenishment rules) and accelerate the flow of products in the supply chain thanks to the exchange of information (EDI, but mainly VMI) of large entities. The manufacturer or the main vendor is the leader, while retailers are the passive followers (Taleizadeh, Noori-Daryan, and Cárdenas-Barrón, 2015). This is particularly important when the exchange of information takes place between the main market players (e.g. the main wholesalers with a combined leading market share and the manufacturer), which allows for a common visualisation of global demand for the entire market.

Given the fact that the demand of the recipient is almost never known and its high volatility, the stored inventory is primarily the safety stock but with possibility to reduce it.(Mazur and Momeni, 2018) Safety stock is a reflection of the company's uncertainty regarding the accumulated demand of customers (in practice, it is the resultant of product shortage risk management based on the forecast error history – demand planning). The greater this uncertainty, the greater the company's stock should be, so as to avoid the usually much larger problem which is not reacting quickly enough to customer needs, especially in a highly competitive market. An ageing stock is also commercially less attractive and may need to be disposed of. Therefore, it is necessary to balance between the risk of not responding to customer needs and the risk of losing the attractiveness of the stock produced (imported) in advance.

The attention directed to this balance, i.e. inventory policy strategies, is increasing with the tightening competition and better tools and models (mainly forecasting) of data management. However, it is difficult to translate expenses on the quality of inventory management into specific effects in the form of increasing cost or process efficiency (Eroglu and Hofer, 2011). This is because, among other things, in addition to the direct indicator of frozen capital, proper inventory management makes it possible to develop savings or improve processes by other departments of the company (cause and effect and the need to compete within the organisation for attribution of merit hinder the possibility of analysing the issue).

Inventory control is a stock management process that bases decisions related to the level of inventory on restrictions resulting from the boundary conditions of factors (quantitative type) which translate into the risk of shortage, resulting in not handling customer orders within the required (through competition for the customer) deadlines. The inventory resulting from the above factors is then modified based on purely business decisions regarding non-quantifiable (qualitative) indicators. Such factors include rare Black Swan events the impact of which on the inventory is determined on the basis of the experience of the managerial staff. Factors that cannot be predicted are mainly political decisions and random events such as the United Kingdom's exit from the European Union – Brexit or the Covid-19 pandemic.

Due to the reliance on external logistics operators and the relative ease of optimisation of transport costs (fleet composition and size), in the case of a predetermined customer base (structure and routing) and frequency of delivery (inventory policy) (e.g. supplying warehouses by the manufacturer once a week), many companies have highly efficient logistics. On the other hand, due to the high cost of building a warehouse (or a factory) in relation to the cost of stock storage, the problem of optimal customer supply (routing) with an optimised variable number and location of warehouses (uncapacitated fixed-charge location problem (UFL)) usually does not include the impact of the cost of stock storage. The routing problem, i.e. Multi-Depot Vehicle Routing Problem (MDVRP), is therefore usually solved first in isolation from the inventory problem, assuming no influence on the strategic decisions regarding the location of the supply points (location problem).

Inventory Routing problem, i.e. simultaneous management of the transport fleet and delivery schedule while supplying geographically dispersed customers from a single central warehouse, is not so problematic. Apart from the rare situation when the capacity of the customer's warehouse is an additional factor (Popović et al., 2012), there is only one basic factor in logistics, which is the limited capacity of the means of transport (with the proviso that each route must start and end in the supplier's warehouse). The whole difficulty of the problem usually shifts to the optimisation of the order size and selection of the right delivery date for a new inventory, which in turn transfers the problem to the level of demand forecast management.

Some of today's regulatory trends related to the environment can significantly affect the profitability of some inventory control strategies. First of all, these are the environmental costs of the entire life cycle of the product, LCA – Life Cycle Assessment (production, distribution, consumption, end-of life recycling or disposal), which can be added to the final price in the form of a carbon tax on the product.

Increasing demands for shorter delivery times and smaller production batches across the economy (especially for goods requiring refrigeration) lead to increased CO_2 emissions

(Scope 3 type emissions) owing to the need to deliver small quantities of the product more frequently and keep small warehouses closer to the customer (due to the decreasing surface area relative to the volume, the cooling capacity of warehouses with the same technology strongly depends on their size). For this reason, the inclusion of additional costs associated with increased emissions in the reduction of delivery times, depending on storage conditions, is one of the ways to have a global and coordinated impact on reducing CO2 emissions.

The emergence of the CO2 emissions trading system (strict carbon caps, carbon tax, and cap-and-offset, cap-and-price, cap-and-trade mechanisms) increases the operating costs of enterprises (Hua et al., 2011b) in the form of a new type of taxation. These direct actions complement the indirect market-based method of reducing emissions. The system of informing the final recipient of products based on certificates of reduced or zero CO2 emissions leads to a competitive advantage of low-emission entities in a carbon-conscious society. As a result, in carbon footprint management, where the limit of emissions is adopted for the entire company, the permitted CO2 emissions are distributed in terms of the ratio of the potential profit from each SKU per unit of CO2 emissions. If it is necessary to purchase additional emission rights, they are part of the BOM (Bill of Materials) of each SKU, as if CO2 were a kind of raw material (resource) that makes up the product (where this raw material, like production substrates, is bought at a changing market price). All of the above can lead to increased cooperation between entities in the supply chain.

3. Inventory Control Dataset description

The dataset of SCOPUS articles searched by keyword “inventory control” and it resulted in 10,201 rows and 35 columns describing articles published over 59 years. For further analysis, 9,829 (96.3%) of them were used.

The rejection of 372 items was associated with:

1. Separator errors, in cases where the following words were found in the citation count column: “Article”, “English”, while the column of the year of the article publication contained the word “s/n”.
2. Missing authors, in cases where the column of authors' surnames contained the word “Anon”, while in the ID column of the authors' surnames, the following sentence was found: “[No author id available]”.
3. No year of publication, in cases where the column of the year was empty.
4. Inconsistency between the number of authors based on surnames and IDs.

Out of the articles analysed, 2,167 did not have a DOI number, whereas 1,973 did not have a single citation. Due to problems with the separation of authors, occurring with additional separators next to suffixes, the following have been removed from the column of authors' surnames: “Jr.”, “Sr.”, “II”, “III” and “Editor”. Then, 13,255 unique IDs of the authors' surnames were listed. The database of articles is divided into decades on the assumption that each starts from year one instead of year zero.

In addition to the surnames of the authors, the article keyword column (the “Index Keywords” column) was also analysed, which resulted in finding 24,891 unique items (after removing the spaces before and after the keyword). Statistical analysis was performed using Jupyter Lab in the Python 3 programming environment. Due to the variety of unique values, the most challenging technical difficulty was the separation of keywords. During this operation, the article database increased to 579,911 rows of data.

To use machine learning methods, data must be presented in a simple form, e.g., tables, sequences of text or sound, or images, as all of these forms have a strictly defined structure and a specific size. In addition, it is assumed that each element is independent of all other elements (it can be isolated from the dataset).

4. Methodology

4.1 Problem statement

The aim of our research is to learn an effective predictive function whose input can be abstract text, keywords of the article, and information on articles cited by it. It should classify each article among the highly cited (top percentile of the number of citations) or lowly cited articles (the rest of articles). We frame the problem as a classification task in which we want to assign an article to a class in terms of citations. The second type of problems that can be considered in relation to the set of articles used are regression tasks. In this case, we want to obtain a number or a set of numbers, e.g., in order to simplify the model, it can assign the number of citations to articles instead of predicting the exact number of citations.

Our goal is to find out what features of the title, abstract, keywords and position in the citation graph make an article likely to be highly cited. The exact number of citations is not important in a such defined problem. This model could be applied directly to predict whether a newly added document will be trending. Furthermore, we can try to explain what features were most important in the decision-making process. It can be later used to interpret which keywords and relations to other articles in the dataset make the paper fit a relevant topic in a given field of science.

In our approach, in order to capture the most important keywords in the IC area, we propose a research scheme covering two principal stages. The first one involves the processing and statistical analysis of the article database in order to identify the most important keywords and the authors who have made the greatest contribution to the development of the intellectual structure. This stage can be treated as a general recognition of the intellectual structure of the IC research. It is significant because in-depth analysis of the database makes it possible to eliminate errors in it, which directly affects the quality of the research results obtained at this stage. In the second stage of the research, we used the “cleaned” database for analysis with the use of deep learning methods.

4.2. Model architecture

Encouraged by their success in many fields, we have decided to use methods based on deep learning in our research. Deep learning is a branch of machine learning - the study of models that improve automatically through experience gained on data. Deep learning focuses on neural networks - a collection of connected nodes called neurons, which loosely models the human brain. The signal in an artificial neural network is the real number transmitted between neurons. Each connection has a weight that is automatically adjusted during the training process. It can increase or decrease the strength of the signal. The output of each neuron is computed by some nonlinear function. Typically, the updates of weights of connections during training are computed using the backpropagation algorithm.

The structure of the network of neurons and the type of calculations can be adjusted depending on the problem. Neural networks specialised in solving problems on data that form graphs are called Graph Neural Networks (GNN). GNN operate on data composed of graph **G** and a set of node and edge features.

The graph **G** is tuple (V, E) consisting of a vertex set vi V and an edge set ei E. Given a feature of node vi denoted by fiRNa graph, convolution operator g:G R| V|N G R| V|M is defined as g(vi)= aggregation ({Wi,j fj | vj G(vi) }), where G(vi) is neighbourhood of node vi in graph G. The *aggregation* function could be, for example, *sum*, *max*, *min* or *mean*. Wi,jRNM is a trainable weighting kernel transforming the graph's N-dimensional features to M-dimensional ones.

Graph convolution operators can be stacked forming consecutive layers of a neural network. Adding more layers (i.e. k layers) allows each node to aggregate more information from neighbours k hops away. However, too deep models may perform worse than simpler neural networks. This is caused by propagating the noisy information from an exponentially increasing number of expanded neighbourhood members or overfitting due to too large a number of model parameters.

In our model, we have decided to utilise the Graph Attention Network (GAT) architecture which belongs to the family of GNNs (Wu, Sun, Sun, and Sun, 2021; Zhao and Feng, 2022). In earlier bibliometric studies, the GNN was used to a limited extent. There are few research results that use neural networks to analyze datasets describing the intellectual structure. Liu, Tsai, Bhuiyan, and Yang (2020) propose a new methodology for whitepaper analysis by designing a heterogeneous graph neural network, named S-HGNN. They use the Heterogeneous Information Network (HIN) using heterogeneous objects and relationships extracted from the whitepaper to obtain similarity measures. Then, they use the Graph Convolutional Network (GCN) and the Graph Attention Network (GAT) to integrate both structural information and internal semantics into the whitepaper embedding. (Grodzinski, Grodzinski, and Davies, 2021) used a neural network for bibliometric analysis of 1,674 scientific papers in the DCM (Degenerative Cervical Myelopathy) field. As a result of the research carried out, a coauthorship network was created. In their studies to detect research topic trends by author-defined keyword frequency (ADKF) (Lu et al., 2021) used four common supervised machine learning approaches: linear regression model (LR), k-nearest neighbor (KNN), eXtreme Gradient Boosting (XGBoost) and random forest (RF).However, these are more standard approaches to bibliometric analysis compared to the GAT, in which the model was structure-aware.

The GAT uses powerful attention mechanism on the node features and modifies the weighting kernel Wi,j=i,jW, where i,j=softmax(mlp([Wfi, Wfj])). It proved to be highly beneficial in many graph tasks. Our data consist of ~1,000 articles forming a directed graph, where articles are nodes and citations are edges. The edge between node a and b exists, if a cites b.

In our research, however, we wanted to use dependencies (mutual citations) between articles. Instead of focusing on each article separately, we preferred to consider each article along with its relationships with other articles. In mathematical terms, a set of articles together with citation relationships forms a graph. The graph can take any structure, because of which standard machine learning methods do not apply. In particular, the vertices of the graph can have any order (there is no such thing as the beginning of the graph). The model to process such a graph should therefore be invariant due to the order in which articles are processed. There is also no such thing as the "locality of information" – relations between articles can be very distant, clusters of vertices dependent somehow on other clusters can form etc. The graph method of machine learning should therefore be able to use information from local relationships, aggregate them into further relationships and also be able to find nonlinear dependencies. The first simple model to have these characteristics was the Graph Convolution Network, "Spectral Networks and Deep Locally Connected Networks on Graphs", which is a generalised version of a convolutional neural network (mainly used for image processing) where the number of nodes can change and they can be disordered. Our work uses a modified version of this 2018 approach called the Graph Attention Network. This modification consisted in adding attention to the model. It was given the ability to increase or decrease the weight of the connection between the vertices of the graph based on the trainable layer using information about the features of these vertices. These models had wide application in the classification of graph vertices based on their neighbours, classification of entire graphs and visualisation of graphs (https://arxiv.org/pdf/2106.12839.pdf). In practice, they have also been used, for example, to forecast road traffic (travel time from one point to another https://arxiv.org/abs/2104.13096), or to predict the chemical properties of molecules https://www.nature.com/articles/s41524-021-00554-0. The open-source implementation of the GAT model by the original author which we used is available at https://github.com/PetarV-/GAT. This Python implementation has been widely adopted and cited in numerous research papers, demonstrating its robustness and credibility within the research community. This implementation could be easily used to reproduce our results or delve deeper into the functionalities of the GAT model within bibliometric analysis.

In our research, we have used automatic term extraction (ATE), i.e., the automatised identification and extraction of terms from domain-specific corpora. From the available text extraction methods, we have selected the TF-IDF (Term Frequency-Inverse Document Frequency). It is a term weighting method with word representation vectors, which creates efficient distributed word vectors and representation learning (Mee et al., 2021; Patil, 2022; Rani and Lobiyal, 2021). The feature fiRN of node i is defined as a normalised vector of TF-IDF measures for 1,000 most relevant words (according to this metric) in abstracts of all articles. How our network works is shown in Figure 2.

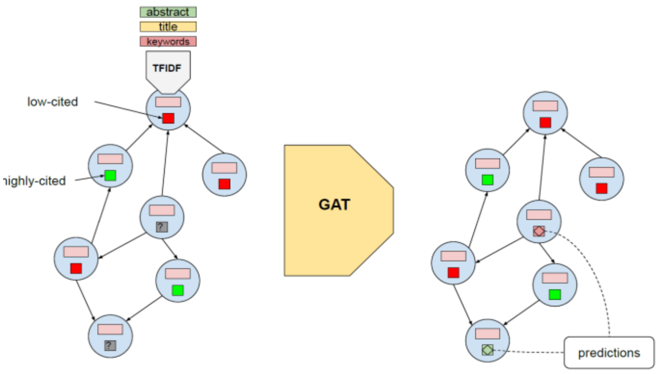

Fig. 2. Mechanism of a neural network used in research

We base the node target labels on whether it fell above or below a 75 %-ile rank. For example, if a 75%-ile rank threshold resulted in a count of eighty, the papers with citations greater than eighty would be labelled "1" and the rest "0". Thus, we are classifying the top 25% most-cited papers for each year in the graph in this example. Formally, our GAT neural network g(vi,f,G) model posterior p(Li=1 | G, f) where Li is the indicator function of whether node i is trending. We train our model on 75% randomly chosen articles in the graph, and test the model on the remaining 25% articles.

4.3. Model Explanation

In order to explain the predictions of our model, we use the SHAP Values technique (SHapley Additive exPlanations)(Lundberg and Lee, 2017). The method we used to explain how networks work is a basic tool for explaining complex machine learning models. This is the most basic method that describes the results obtained from a neural network. Its two main advantages are global interpretability (i.e., which features have the greatest positive or negative impact on the model response) and local interpretability, as using this method we can explain which features were taken into account when predicting a particular example from the data. An alternative to this method is, for example, the LIME https://arxiv.org/abs/1602.04938 which, however, is an older tool and, in theory, gives worse results. The subject of interpretability of neural networks is developing very dynamically, but so far, no other method has given such good results nor is as general as the methods mentioned above. The SHAP value is a unified measure of feature importance. Shapley values refer to a conditional expectation function of the original model. SHAP values provide the unique additive feature importance measure that can be used for local and global interpretability. For example, we can calculate SHAP values for each observation.

Using this method, we can explain why a case receives its prediction and the contributions of the predictors. Furthermore, collective SHAP values can show how much each predictor contributes, either positively or negatively, to the target variable. This is like the variable importance plot, but it is able to show the positive or negative relationship for each variable with the target. For each article, we can calculate SHAP values corresponding to specific words in the abstract. Features that push the prediction higher (i.e., the article is more likely to be trending) are shown in red, and those pushing the prediction lower are in blue.

5. Results

5.1. Statistical analysis

Statistical analysis was aimed at learning about the keywords that were found in the largest cumulative number of citations. In addition, we have presented the most cited authors. In the perspective of the entire database, the 20 most frequently cited authors' surnames and the most frequently cited keywords are shown in Table 1.

Table 1. Top most cited Authors and Top most cited Keywords

Top 20 by citations					
Top 20 most cited Authors			Top 20 most cited Keywords		
Authors Name	Cited by	Percentile	Keywords	Cited by	Percentile
Canchon G.P.	4202	1	inventory control	223053	1
Lee Hau L.	3894	1	mathematical models	60926	1
Goyal S.K.	3159	1	production control	46240	1
Gallego Guillermo	2457	1	costs	43028	1
Quyang L.Y.	2335	1	optimization	40955	1
Semchi-Levi D.	2186	2	industrial management	29286	1
Lariviere M.A.	2085	2	scheduling	28142	1
Van Ryzin G.	2031	2	supply chain management	27961	1
Disney S.M.	2013	2	inventory	27034	1
Towill D.R.	1933	2	decision making	26968	1
Cárdenas-Barrón L. E.	1828	3	strategic planning	23452	2
Sarker B.R.	1826	3	sales	21905	2
Chaudhuri K.	1778	3	operation research	18902	2
Cheng T.C.	1730	3	marketing	18882	2

Tang Christopher S.	1715	3	Computer simulation	18311	2
Wee H.-M.	1660	4	Inventory management	18093	2
So K.C.	1638	4	Industrial economics	17637	2
Chen F.	1636	4	Supply chains	17616	2
Wu K.-S.	1571	4	Algorithms	16888	2
Teng J.-T.	1541	4	Production engineering	16036	2

Inventory control is the most frequently quoted keyword in the processed database. This confirms the key place of inventory control in supply chain management research. To illustrate the variability of interest in the main keywords in the last decade, in the first decade of the 21st century, the 5 most important words were selected in terms of cumulative citation numbers except IC). This omitted the search key of the dataset, "inventory control", for which the number of results is significantly higher (its frequency of citation over the years may be disturbed by the search algorithm). Throughout the database since 2001, the cumulative citation counts for the most important 5 keywords in the last decade (2011-2020 inclusive), with the exception of the keyword "inventory control" in a given year, are shown in Figure 3. In our analysis, we used IDs of authors, while in the presentation of results, we limited ourselves to the names of the authors in order to increase their readability. (except IC). Among the top ten articles from the entire inventory control database (with keywords from the last decade), we can find the following: (An and Huang, 2006; Benjaafar et al., 2013; Cachon and Fisher, 2000; Cachon and Lariviere, 2005; Coelho et al., 2014; Gallego and Ryzin, 2013; Hua et al., 2011b; Kapuscinski, 1996; Lockett and Wright, 2005; Metters, 1997). In parentheses next to the keywords, the total number of citations in the last decade is given. Throughout the entire database with a breakdown into decades, the list of the most important authors is shown in Table 2.

In parentheses next to the authors' surnames we provide the total number of citations in a given decade. The authors with the same number of cumulative citations are separated by an "and". The list of the most important keywords is shown in Table 3 with a breakdown into decades throughout the entire database. In parentheses next to the keywords, the total number of citations in the given decade is given. Keywords with the same number of cumulative citations are separated by an "&".

To illustrate the variability of citations of the most important authors, in the last two decades, we have shown the cumulative number of citations listed next to the global ranking of the most important authors for the entire database (along with the percentile of positions in the entire list). Throughout the entire database, the cumulative citation counts for the most important authors and keywords are shown in Table 4.

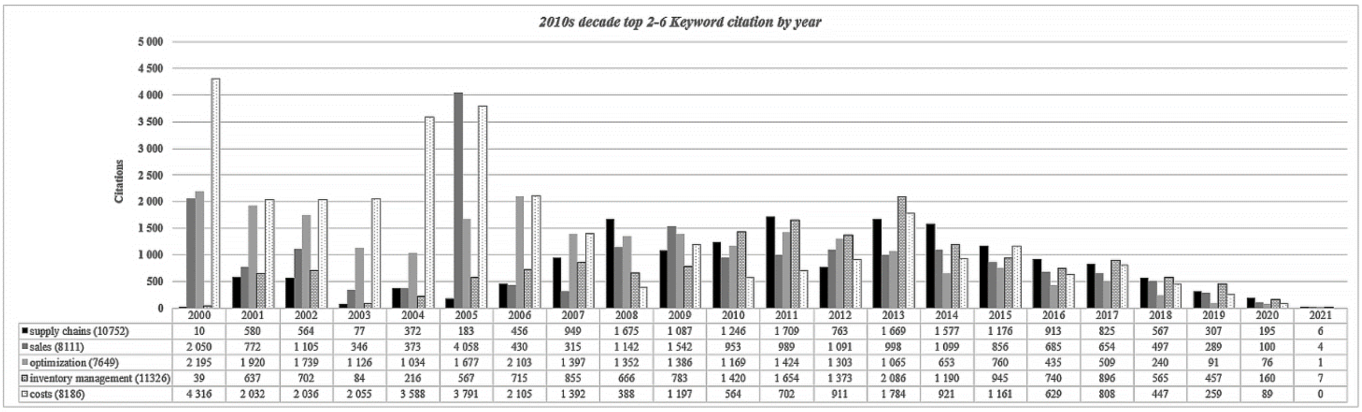

Fig. 3. Cumulative citation counts for the 5 most important keywords except "inventory control"

Table 2. The most important authors

Top 10 most cited Authors by decade							
	1960s	1970s	1980s	1990s	2000s	2010s	2020s
1	Fan L.T. (7) &Elmaneh J. (7)	Philip G.C. (845)	Newell William T. (703)	Hopp W.J. (851)	Cachon G. P. (3315)	Benjaafar S. (1053)	Gharaei A. (129)
2	Gallagher D.J. (6)	Covert R.P. (602)	Baker Kenneth R. (531)	Woodruff D.L. (744)	Lee Hau L. (2399)	Niaki S.T.A. (745)	Hoseini Shekaribi S.A. (125)& Karimi M. (125)
3	Pegels C.C. (5)	Misra R.B. (269)	Monaham James P. (489)	Raafat F. (720)	Lariviere M.A. (1589)	Laporte G. (708)	Ivanov D. (54) & Rozhkov M. (54) & Dolgui A. (54)
4	Sinha B.K (3)& Gupta S. K.	Nahmiasj S, (154)& Rivera H. (154)	Glassey C.R. (425)	Aggarwal S.P. (704)	Frohlich M.T. (1481)& Westbrook R. (1481)	Coelho L.C. (698)	Shaikh A.A. (39)
5	Lewis H.S. (2) & Self G.D. (2)	Henery R.J. (88) & Ladany S.P. (88)	Dave U. (406)	McGill J.I (693)	Fisher M. (1353)	Li Y. (634)	Cardenas-Barron L.E. (35)

6	Disney R.L. (1) & Knezevich S.J. (1)	Sternlieb A. (86)	Resende M.G.C. (356)	Pearson J.N. (658)& Carr A.S. (658)	Towill D.R. (1335)	Daskin M.S. (626)	Hilary G. (34) & Babich V. (34)
7		Skeith R.W. (73)	Patel L.K. (312)	Emmons H. (485)	Drezner Z. (1269)	Wang S. (528)	
8		Taha H.A. (63)	Wong Danny S. (300) & King Barry E. (300)	Vokurka R.J. (395)	Wu K.-S. (1204)	Cordeau J.-F. (505)	
9			Burns L.D. (294)	Bassok Y. (378)	Hendricks K.B. (902)	Glock C. H. (490)	
10						Hua G. (479)	

Table 3. The most important keywords

Top 10 most cited Keywords by decade							
	1960s	1970s	1980s	1990s	2000s	2010s	2020s
1	Inventory control (11)	Inventory control (4118)	Inventory control (22252)	Inventory control (55370)	Inventory control (104940)	Inventory control (35640)	Inventory control (722)
2	Production planning and control (9)	Production control (1760)	Production control (8582)	Mathematical models (24504)	Mathematical models (33428)	Inventory management (11326)	Supply chains (201)
3	Operations research (6) & Poisson proces (6)	Operations research (744)	Mamagement science (3735)	Optimalization (16693)	Costs (22900)	Supply chains (10752)	Inventory management (167)
4	E c (3)	Industrial management (218)	Technological forecasting (3209)	Production control (14749)	Supply chain management (19959)	Costs (8186)	Supply chain (156)
5	Mat (2)	Decision theory and analysis (213)	Operations research (2488)	Scheduling (14136)	Industrial management (19639)	Sales (8111)	Optimisation (131)
6	Bioengineering, computer applications (0) & computers (0)&medical equipment and supplies (0)	Inventory control – mathematical models (151)	Scheduling (2294)	Costs (11845)	Production control (18882)	Optimisation (7649)	Sales (104)
7		Mathematical statistics (104)	Economic order quantity (1709)	Strategic planning (9468)	Decision making (17674)	Supply chain management (6067)	Costs (89)
8		Industrial engineering (100)	Decision theory and analysis (1660)	Industrial management (8202)	Optimisation (15929)	Inventory (5765)	Sensitivity analysis (88)
9		Scheduling (99)	Mathematical models (1630)	Marketing (8035)	Strategic planning (13834)	Decision making (3775)	Decision making (78)
10		Inventory replenishment (88)	Inventory (1560)	Operations research (7824)	Inventory (13022)	Stochastic systems (3588)	Optimisation (77)

Table 4. Cumulative citation counts for the most important keywords

Top 10 by citations by decade											
Authors name	Decade	Cited by	Rank	Global Rank	Percentile	Keyword	Decade	Cited by	Rank	Global Rank	Percentile
Benjaafar S.	2010s	1053	1	22	5	inventory control	2010s	35640	1	1	1
Niaki S.T.A.	2010s	745	2	71	14	inventory management	2010s	11326	2	16	2
Laporte G.	2010s	708	3	73	14	supply chains	2010s	10752	3	18	2
Coelho L.C.	2010s	698	4	81	16	costs	2010s	8186	4	4	1
Li Y.	2010s	634	5	82	16	sales	2010s	8111	5	12	2
Daskin M.S.	2010s	626	6	25	5	optimization	2010s	7649	6	5	1
Wang S.	2010s	528	7	101	20	supply chain management	2010s	6067	7	8	1
Cordeau J.-F.	2010s	505	8	127	25	inventory	2010s	5765	8	9	1
Glock C.H.	2010s	490	9	131	26	decision making	2010s	3775	9	10	1
Hua G.	2010s	479	10	135	26	stochastic systems	2010s	3588	10	89	9
Cachon G.P.	2000s	3315	1	1	1	inventory control	2000s	104940	1	1	1
Lee Hau L.	2000s	2399	2	2	1	mathematical models	2000s	33428	2	2	1
Lariviere M.A.	2000s	1589	3	7	2	costs	2000s	22900	3	4	1

Frochlih M.T.	2000s	1481	4	24	5	supply chain management	2000s	19959	4	8	1
Westbrook R.	2000s	1481	4	24	5	industrial management	2000s	19639	5	6	1
Fisher M.	2000s	1353	5	28	6	production control	2000s	18882	6	3	1
Towill D.R.	2000s	1335	6	10	2	decision making	2000s	17674	7	10	1
Drezner Z.	2000s	1269	7	30	6	optimization	2000s	15929	8	5	1
Wu K.-S.	2000s	1204	8	19	4	strategic planning	2000s	13834	9	11	2
Hendricks K.B.	2000s	902	9	51	10	inventory	2000s	13022	10	9	1

5.2. Experiment

Preparation of the dataset

Using a collection of articles for the keyword "inventory control", we have conducted an experiment to determine the words that set trends in the development of intellectual structure in this area. The experiment included several stages that allowed us to create a list of keywords throughout the decades in which the research was conducted. The entire research period covering the years 1950-2021 was divided into 4 periods. To simplify the interpretation of the results, we have combined the first four decades covering the years 1951-1990. First, we prepared a dataset by loading tabular data using a Python script. Then, we generated a list of links between the articles. For each article title ("A"), the dataset was searched to see if it appeared in the "Cited articles" column for other publications. If so, the article found was marked "B" and a link from B to A was added to the list of citations. The created list was the list of edges of the directed graph analysed in the subsequent steps. Next, for each article, we prepared a vector of fiRN features (where N=1000) and replaced the abstract for each article with a list of words it contained. From each list, we removed "stop words", e.g., the, is, at, which, on etc. We used the "Porter Stemming Algorithm" to process each word. Each word was replaced with its stem, e.g., argue, argued, argues, arguing, and argus are replaced with "argu" (Table 5).

Table 5. Examples of transformations of base words into stems in the examined set of articles

Base words	Abbreviation
['reservation', 'reservations', 'reserve', 'reserved', 'reserves', 'reserving']	'reserv'
['this']	'thi'
['general', 'generality', 'generalization', 'generalizations', 'generalize', 'generalized', 'generalizes', 'generalizing', 'generally', 'generate', 'generated', 'generates', 'generating', 'generation', 'generations', 'generative', 'generator', 'generators', 'generic', 'generous', 'generously']	'gener'
['proposal', 'proposals', 'propose', 'proposed', 'proposes', 'proposing']	'propos'
['inventoried', 'inventories', 'inventory', 'inventorying']	'inventori'
['chain', 'chaining', 'chains']	'chain'
['decision', 'decisions', 'decisive', 'decisively']	'decis'
['was']	'wa'
['comparability', 'comparable', 'comparably', 'comparative', 'comparatively', 'comparator', 'compare', 'compared', 'compares', 'comparing']	'compar'

Each word was assigned a TF-IDF weight. It determined how important a word was for a given abstract in the context of the entire set of abstracts. For example, if a word appeared in every abstract, it would get a low weight. The more often a word appeared in one abstract, the higher the weight. Then, 1,000 words with the highest TF-IDF weight were selected and arranged in list L. For each abstract, a feature vector with a length of 1,000 was created. The value in the ith place was equal to the TF-IDF weight if the word L[i] appeared in this abstract. Otherwise, 0 was assigned. The next stage of the experiment was to assign a class to each article. If the percentile 75% of the number of citations of articles was 150, then, the articles with more than 150 citations were assigned class 1 and the remaining ones, class 0. In the last stage of database preparation, we divided the dataset into a training and test part. The training was conducted on 75% of randomly selected articles, and the model was tested on the rest.

5.3. Preparation of the neural network

In our research, we used a ready-made GAT neural network implemented in the Pytorch Framework, with two layers and 8 heads. Dropout for better generalisation was set to 0.2. Adam optimiser with lr=5e-3 (Krishna Bhargavi et al., 2019) was used for training. Regularisation for weights 5e-4 was also added. On the training set, the model was trained using the cross-entropy loss function. We used the "Transductive" setting which makes the entire graph available to the network during training, but only labels of articles from the training set were used. Figure 4 shows the graph of the effectiveness of the model after successive training epochs, where the blue line is training set and the yellow line - the test set.

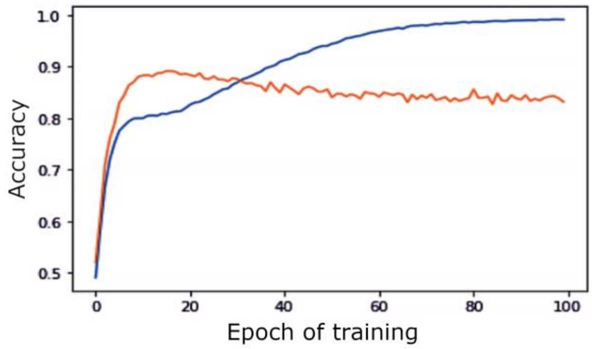

Fig. 4. Model effectiveness chart

Due to overfitting, the "early stopping" technique was used and in the further part of the experiments a model from the 20th training epoch was used, obtaining an average test set effectiveness of 88%. To explain the neural network, we used the SHAP Values technique and the official implementation https://github.com/slundberg/shap. We used the Kernel SHAP technique (Aas, Jullum, & Løland, 2021). We calculated the SHAP values for each of the 1,000 words in the feature vector for each article in the dataset. The sampling rate was set to 100. Table 6 presents mean SHAP values. Figures 5-8 present the visualisation of the SHAP values of selected articles and the most important global values.

The model we have created is a function that adopts an article citation graph at the input (which article quotes which one) within the subset of articles we are considering. A subset of the words that appear in the abstract of each article (as described above) is created by selecting 1,000 words from all abstracts that we have in the database based on the TF-IDF measure and then, we provide the model with information on which of these words can be found in each abstract separately. The model returns the number p [0.1] which can be interpreted as the probability that the article belongs to the frequently cited article class.

The beeswarm plot is designed to display an information-dense summary of how the top features in a dataset impact the model's output. Each instance of the given explanation is represented by a single dot on each feature fow. The x position of the dot is determined by the SHAP value of that feature (the importance of that feature for model prediction), and dots "pile up" along each feature row to show density. Colour is used to display the original value of a feature (in our case it is the tf-idf value of a given word). Red describes the greater value and blue the lesser one. The words are sorted by the mean absolute value of the SHAP values for each feature. This order places more emphasis on broad average impact, and less on rare but high magnitude impacts.

Table 6. Mean SHAP values 1950-2020

1950-1990	**1991-2000**
research (+0.26)	thi (+0.24)
franci (+0.23)	polici (+0.24)
model (+0.22)	model (+0.21)
materi (+0.19)	optim (+0.14)
paper (+0.14)	determin (+0.11)
result (+0.13)	inventori (+0.1)
comput (+0.13)	implement (+0.1)
level (+0.13)	compar (+0.1)
use (+0.12)	problem (+0.09)
problem (+0.12)	paper (+0.09)
2001-2010	**2011-2020**
elsevi (+0.45)	elsevi (+0.65)
thi (+0.22)	thi (+0.24)
model (+0.17)	gener (+0.17)
compani (+0.14)	propos (+0.17)
decis (+0.13)	studi (+0.14)
inform (+0.12)	paper (+0.13)
research (+0.1)	problem (+0.13)
time (+0.09)	demand (+0.13)
chain (+0.08)	exampl (+0.12)
paper (+0.08)	sever (+0.11)

For example, in the years 1990-2000 the decisions of the model were very much influenced by the word "polici". In articles, the word appeared rarely or not at all and in these cases it received a SHAP value close to 0, which means that then it had little impact on the model's decisions. However, if it appeared in the article more often (red colour), it is assigned a positive SHAP value, and therefore it had a major impact on the assignment of frequently cited articles to the class.

The assignment of frequently cited articles to the class was also influenced by the more frequent occurrence of the words polici, compar, literatur, chain. On the other hand, the assignment to a negative class was strongly impacted by the occurrence of the words determin, implement, paper, requir. In the years 2011-2020, the keyword "elsevi" was particularly important. Where it was common, the model was more likely to rate the articles as more cited, while the generally rare occurrence or absence of the word resulted in a tendency to rate the article as less frequently cited. However, there have been a few instances where the rare occurrence of the word has been used by the model as an indication that the article is cited more often (this is indicated by a group of blue dots on the right side of the graph). The word "reserv" had a very similar impact on the model's evaluation, although its impact was both positive and negative. As in the previous decade, the more frequent occurrence of the word "thi" resulted in a more negative response of the model. The words "gener", "propos", "uni" had a similar impact in this decade.

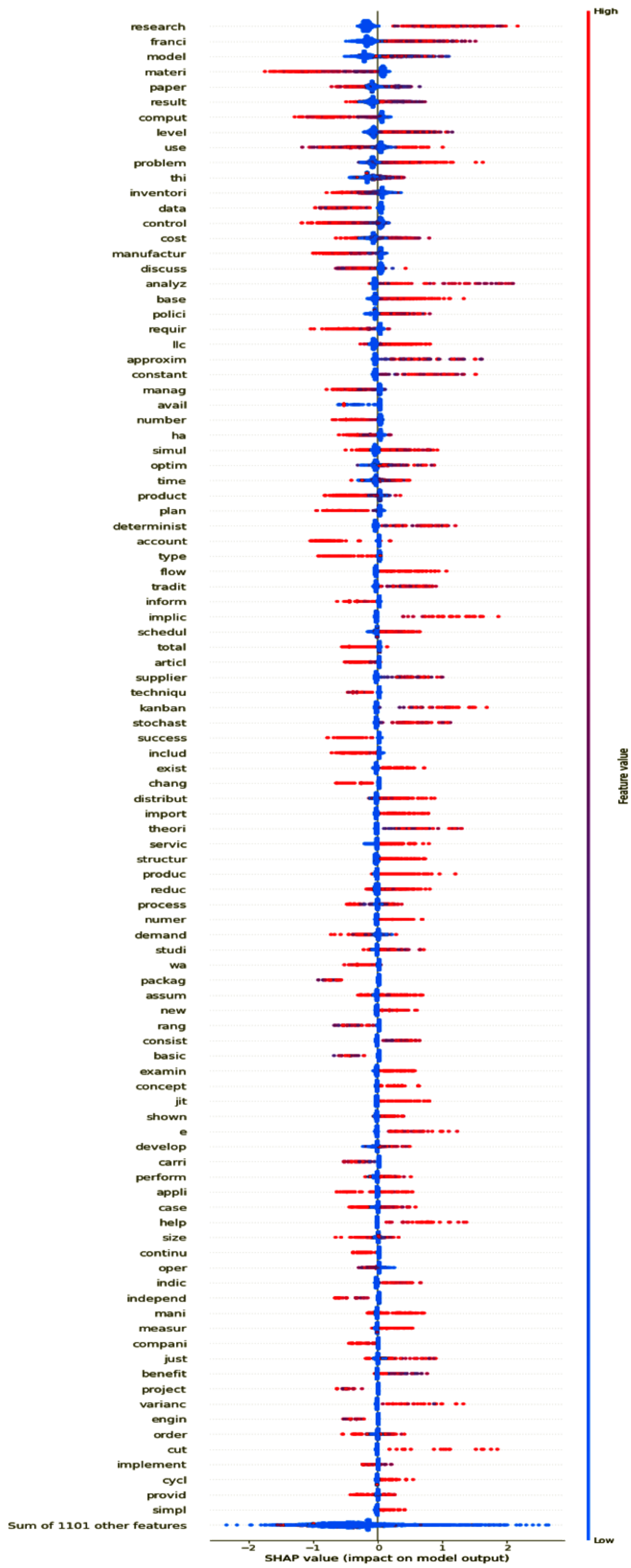

Fig. 5. Beeswarm 1950-1990

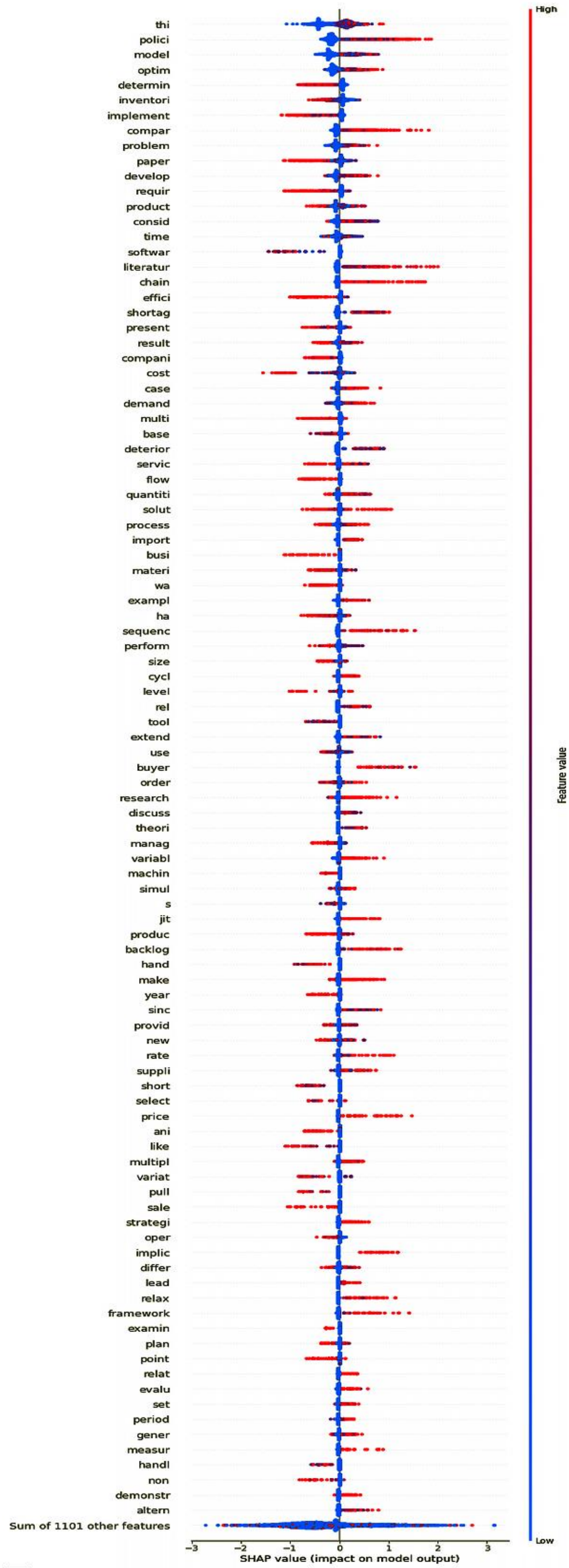

Fig. 6. Beeswarm 1991-2000

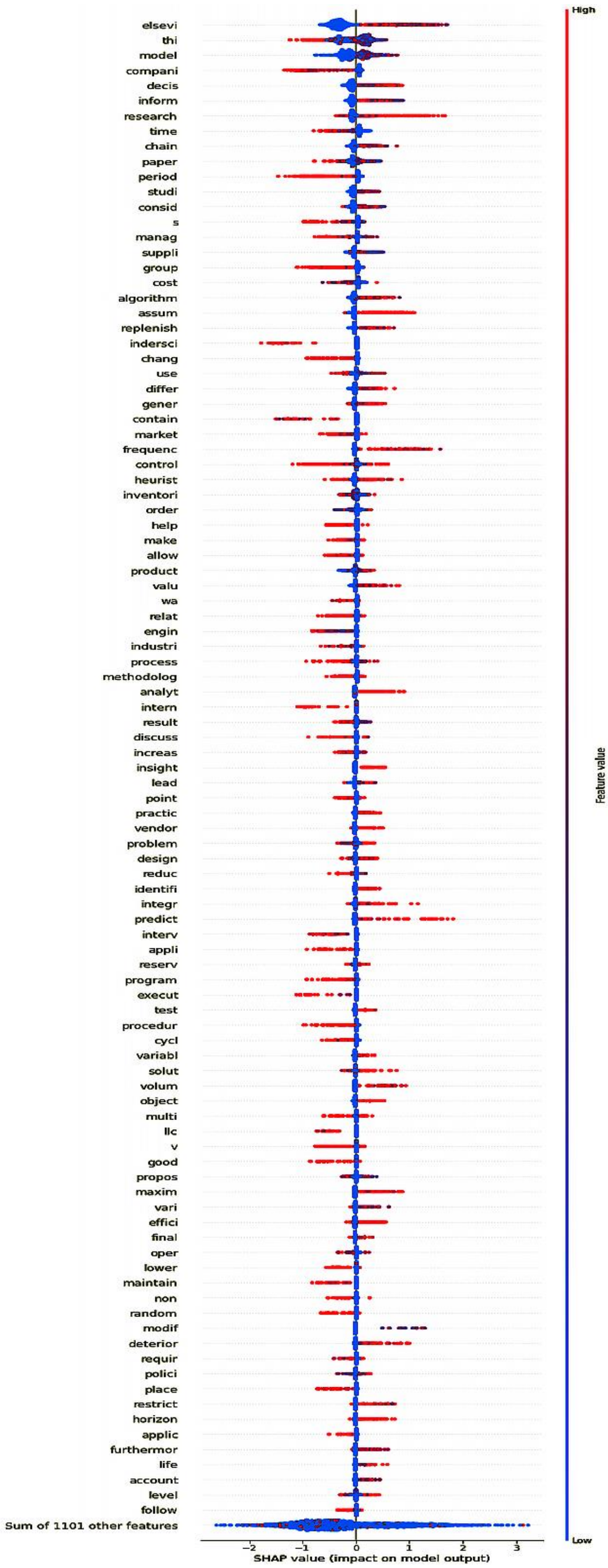

Fig. 7. Beeswarm 2001-2010

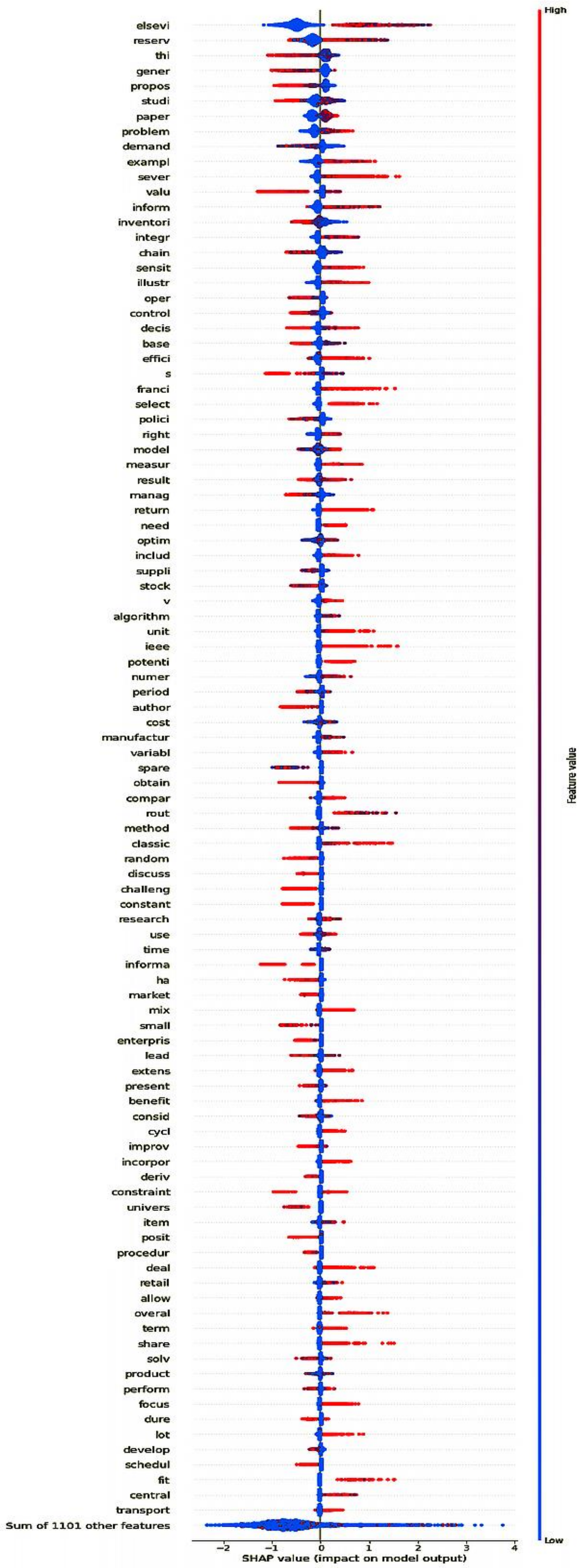

Fig. 8. Beeswarm 2011-2021

Beeswarm charts show that almost every keyword has the greatest impact on the model's response when they appear more often in the article (clusters of blue points are around zero beeswarm values), but in some cases the rare occurrence of the word caused a shift towards a positive or negative response (for example, when the words "research", "franci", "model" occurred in the years 1950-1990, they rarely caused a shift towards a negative answer).

6. Discussion

Current research in the area of logistics and supply chain management uses widely available software for this type of analysis. Although bibliometrics studies the formal properties of the knowledge domain using mathematical and statistical methods, in previous studies the authors have not independently analysed input databases (Ben-Daya et al., 2019; Xu et al., 2018). Rather, they assumed the correctness of the input data for bibliometric analysis. In our research, we independently processed a database describing the inventory control domain by determining the keywords with the highest cumulative number of citations. Unlike in previous studies, we included both authors' keywords and index keywords. Moreover, due to the significant contribution of activities performed by members of research teams, such as thorough review of the literature, the triangulation of research methods does not eliminate subjectivity in the process of inference and synthesis (Chen et al., 2017).

In our methodological approach, we have introduced an additional initial stage consisting in testing the existing results of bibliometric research in terms of their similarity to our analysis. Attention was drawn to the similarity of the methodology of bibliometric analysis used on the set of 11,603 (99%) out of all available 11,716 articles from 49 years available in the SCOPUS for the query TITLE-ABS-KEY database ("bibliom*"). The content of the abstracts was subjected to standard preprocessing consisting of lemmatization and tokenization. Then, using a neural network trained on a large set of abstracts in English, the embedding of each of the abstracts was found. We used the RoBERTa model (https://arxiv.org/abs/1907.11692) based on the transformer (https://arxiv.org/abs/1706.03762) architecture, which is currently the most popular model in natural language processing (NLP). The pre-trained RoBERTa model we utilized is accessible from the Hugging Face repository at https://huggingface.co/roberta-base. We chose this particular model due to its proven performance and widespread adoption in the research community, which is well-documented in numerous studies. In the next step, using the cosine distance, the most similar abstracts were determined. The obtained results indicate that the methodology used so far is not similar to the one proposed in the article. The most methodologically similar articles, using two algorithms determining similarity, are (Hire and Sandbhor, 2020) with a value of 0.9211 for algorithm 1 and (Voltolini et al., 2018) with a value of 0.9890 for algorithm 2, although they do not refer strictly to the IC context. It is also worth noting that slightly lower values were also obtained for a limited group of other articles.

In our research on IC, we have used a different approach based on statistical analysis and deep learning. This has allowed us for an in-depth look at the database exported from the SCOPUS database. Our research has revealed the existence of many inaccuracies and errors in the database describing the intellectual structure of the IC. In the case of using such a database for analysis, for example, in programs such as VosViewer, Gephi or others, we see a real risk of creating an erroneous network of links among keywords, authors or journal titles. Subsequently, this leads to incorrect calculation of the number of citations, e.g., for the most frequently used keywords. As a result, determining the main trends in the directions of research is fraught with errors, which may change the general view of the intellectual structure of a given field of knowledge. In our research, we have accepted only 96.3% of all articles exported from the SCOPUS database for statistical analysis. In our research at the pre-processing stage, we limited ourselves only to rejecting articles that did not have an abstract, the number of citations or could not be matched to the citation graph. In the processed database, there were articles that did not have references to other articles. We assume that with larger datasets describing more general phenomena such as operations management (OM) or SCM, it can lead to even greater difference due to erroneous records in the database. In our analysis, a notable observation is the emergence of the stem 'elsevi', which is the Porter Stemmer abbreviation for the publisher 'Elsevier', receiving high SHAP values for the decades 2001-2010 and 2011-2020. This signifies a distinctive aspect of keyword importance, deviating from the common thematic or topical keywords usually encountered in bibliometric analyses. The prominence of 'Elsevier' in our analysis potentially mirrors the publisher's growing significant role in disseminating research in the field of inventory control during these decades.

We have demonstrated that the proposed methodological approach based on the use of a neural network to determine keywords in the area of inventory control requires high-quality data describing the intellectual structure. In our bibliometric analysis using the GAT, we have created a model that remembered only the most important articles and keywords found in them. This approach truly differentiates between two classes of articles and allows to identify those frequently cited. Consequently, our model has proven to have similar effectiveness on the articles we have used to create it as well as on those it did not see. The GAT network's strength lies in its attention mechanism, which autonomously identifies and weighs the importance of relationships between nodes (papers) based on objective computational assessments, thus minimizing the scope for subjective interpretation. This data-driven methodology ensures a more objective and consistent analysis, contrasting with previous subjective approaches that are prone to biases in identifying research trends and gaps in the inventory control field.

There are also alternative machine learning technologies that could be used in bibliometric analysis. The first of them is a family of algorithms based on Decision Tree Learning. It is based on the automatic creation of decision-making processes on the basis of examples. The decision trees created in this way have a hierarchical structure. This means that a set of objects is divided in a series of steps by answering questions about the value of selected features or their linear combinations. The final decision depends on the answers to all the questions. In order to improve generalisation, many decision trees are often used for one problem to create the so-called random forest. One of the modifications of this approach is the xgboost algorithm which, as practice shows, achieves very good results in many decision problems. The advantage of these methods is also the relatively easy interpretability of the model. However, as the complexity of the data increases, as in our case, where we are dealing with natural language and graph structure of data, decision trees become less effective or generalisation encounters certain problems (Kotsiantis, 2013).

The second possibility refers to the family of simple neural networks (multilayer perceptron). These methods are very effective on complex data. They can find very complex nonlinear relationships in data. However, they require tabular data or data that can be presented in this way. In the case of our research, we wanted the model to use information about the cited articles, which would not be possible in such a simple network (Botalb et al., 2018).

The third option is to use a family of models adapted to natural language processing, for example, based on the Transformer model. These algorithms are very effective in the understanding of natural language (Vaswani et al., 2017). It might seem that such a model could be useful in the processing of analysed abstracts contained in the processed database. However, like ordinary neural networks, it would not use the graph structure of the data we processed. That is why we decided on a much simpler but very popular tf-idf method to simplify the language of abstracts. The simplification of abstracts referred to the selection of the most important words, and the basic model was chosen so that it understood the graph structure of the data. Using the RoBERTa (a variant of the Transformer) model at the initial stage of our method proved that it doesn't return robust enough results on its own. All other stages are important for modeling relations between articles.

When selecting more keywords for a complex intellectual structure, as our research shows, there is the problem of keyword selection. Does the model make decisions based on some simple relationships between these words, or does it perceive more complicated dependencies? The strength of neural networks lies in the fact that they are able to learn any complicated function for a large number of variables (keywords). The neural network itself decides as to which words are more and which ones less important. It does not, however, focus on one word only, but rather takes into account the relationships between words.

By choosing a model that can process data with a graph structure, we have reduced its capacity to understand the information contained in its vertices, i.e. individual articles (Hou et al., 2019) If we wanted to maximise the quality of information extracted from individual articles, families based on “multilayer perceptron” or the aforementioned natural language processing models would work better. However, in creating our model, we wanted to maintain a compromise between focusing on the relationship between articles and the information itself hidden in articles, which is why we chose its hyperparameters so that the “validity” of these two aspects was similar.

The problem with the capacity of the graph model for the information contained in individual articles is not due to limitations in computing power, but the very nature of these models. When increasing the number of their parameters, the stability of training decreases significantly. An additional limitation of the graph model is the limitation on the size of the input data graph. As this size increases, the number of necessary calculations, as well as the need for memory increase significantly. In our case, however, this was not a problem, because the set we analysed was not very large. The network was trained on one standard graphics card. However, if we wanted to analyse larger data set several times, we should use methods that simplify this model and reduce computational complexity by, for example, dividing the graph into fragments.

7. Conclusions

By conducting a statistical analysis, we have proven that over the decades, research in the area of inventory control has undergone fundamental changes. Current research focuses mainly on such keywords as “supply chains”, “inventory management”, “costs”, “sales” or “optimization”. However, since the 2020's, new keywords in the area of inventory control have appeared, such as “advanced analytics”, “cyber physical systems” (cpss), “data analytics”, “embedded systems”, “industrial revolutions”, “industry 4.0”, “information management” or “Internet of things”. This shows that the current theoretical framework for research in the area of inventory control is the theory of supply chain management which includes emerging practical problems.

The novelty of our paper is the use of a GAT network for bibliometric analysis of the inventory control area. Our observations regarding the directions of current research in the area of inventory control are based on the use of universal and objective methods of processing bibliometric data sets. We argue that the subjective approach used many times before in bibliometric research over inventory control does not reveal the true nature of the research conducted and can lead to bias in determining research gaps.

We have considered all articles from the IC area without limiting the analysis to a specific set. We have used a neural network to learn from a specific set of articles and analyse how it works on them and what answers it renders. Bibliometric analysis was limited to articles from the SCOPUS database, including all items in the source, which affected the consistency of the database. We have used a two-step research scheme, including statistical analysis and the use of unsupervised deep learning, which has significantly increased the quality of the study. With the adopted approach, the quality of bibliometric analysis refers to the correct determination of keywords that set the basic research directions in the area of inventory control. Mean SHAP values table and Beeswarm charts show how keywords that affect article citations in the inventory control area have changed. This allows for a holistic view of the intellectual structure of research in the area of inventory control throughout decades. Our research indicates to what extent a given word contributes to an article being frequently cited.

However, our research also has limitations. First of all, we have used a single SCOPUS database as a source of articles about research in the area of inventory control. This does not provide the opportunity to compare the results of keyword analysis with other available databases. In future research, a comparative analysis with other databases could be conducted to validate and potentially broaden the scope of our findings. Secondly, we have limited the research only to articles, omitting other types of publications, which affects the order of keywords affecting the citation of articles.

The use of statistical analysis and deep learning in the area of inventory control has confirmed the possibilities of processing and bibliometric analysis of databases of any type of scientific publications meeting the criteria of big data. Our study focuses only on keywords and there is an opportunity for a more comprehensive and complete look at existing resources in the area of logistics and supply chain management. The potential for future bibliometric research using neural networks is considerable. It can include articles published in individual journals or their groups, multiple databases, which in practice allows to understand the profiling of scientific research due to any characteristics relevant to the academic community as well as managers.

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使用神经网络来检查库存控制中的热门关键词

關鍵詞
库存控制
神经网络
GAT（图注意力网络）
文献计量分析
关键词

摘要
库存控制是物流研究的关键领域之一。利用 SCOPUS 数据库，我们已处理了 9,829 篇库存控制方面的文章，采用统计方法和机器学习的三角法。我们证明了所提出的统计方法和图注意力网络（GAT）架构在确定库存控制研究中的热门关键词方面的实用性。我们通过展示关键词在文章中的演变，演示了 1950 年至 2021 年间研究的变化。我们研究的新颖之处在于采用无监督深度学习进行文献计量分析的应用方法。这允许识别确定文章高引用率的关键词。我们在库存控制研究中提出的研究智力结构的理论框架是通用的，可以应用于任何知识领域。