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Identifying Influential Social Impact Websites with HITS Algorithms

Yang Ruei Jheng, Ping-Yu Hsu, Jiu Zhong Chen, Ming Shien Cheng ✉ & Yu-Chun Chen

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Abstract

Advocators of ESG (Environment, Social, Governance) attempt to propose standards for business to report their sustainability measure to investors. The three aspects are corporate social responsibility in society. However, the indicators to reveal impact generated by social activities are still in the development. As an result, the Social Impact

reported on websites and ESG reports are diversified and inconsistent. This research aimed at recommending model webpages to readers for the references of business world. This research implements variations of HITS algorithm to identify authority and hub pages excluding the influence of pages in the same website as self-references may seriously distort ranking result. Top 10 authority pages are recommended among 3 million webpages collected from the world wide web. The appropriateness of the pages is compared against first 10 links retrieved from Google search. Expert reviewers confirmed that the recommended pages were better than the links retrieved from Google.

Keywords

HITS Algorithm **ESG** **Social Impact**

CSR

1 Introduction

The concept of CSR was already mentioned in the book “Philosophy of Management” by British scholar Oliver Sheldon in 1923. In recent years, the concept of CSR has surfaced again due to the increasing exploitation of the environment and the rising awareness of environmental protection

among the general public (Li Xiuying, Liu Junru, & Vol. 1 [1]). The importance of ESG as an action guideline for CSR is obvious. In a successful company, the “S(Social)” in ESG is about how to implement Social Impact. What kind of social impact do they have on society?

The HITS algorithm has been proven in previous studies to find opinion leaders in social networks (Sun, Bin, & Applications [2]) or to improve the accuracy of recommendation systems (Y.W. Liu & J.L. Huang. [3]). The above studies aim to find the most representative nodes in Internet graphs to find their hidden meaning. In short, the HITS algorithm coincides with this study to find the authority concept of “social impact” in web pages. Therefore, this study used the HITS algorithm to analyze the social impact of each webpage and gave the ranking to find the best social impact criteria.

In this study, we collected many social impact-related web pages from the World Wide Web, modified the graphs, and then implemented the HITS algorithm to find the authority of social impact web pages.

This paper organized as follow: (1) Introduction: Research background, motivation and purpose. (2) Related work: Review of scholars’ researches on HITS algorithm, CSR and ESG, social impact of ESG and Scopus. (3) Research methodology: Content of research process in this study. (4) Result analysis:

Experimental results and the discussion of the test results. (5) Conclusion and future research: Contribution of the study, and possible future research direction is discussed.

2 Related Work

2.1 HITS Algorithm

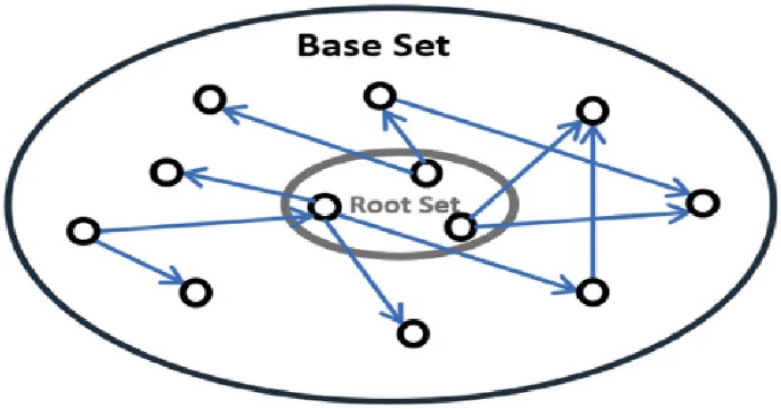
Hyperlink-Induced Topic Search (HITS Algorithm, short for HITS) is a link-oriented graph theory algorithm that is well suited for use in Internet relationships. The HITS algorithm assigns an Authority Score and a Hub Score to each web page and ranks them (Fig. 1). The HITS algorithm has two basic assumptions.

1. A good Authority page will be pointed to by many good Hub pages.

2. A good Hub page will point to many good Authority pages.

These two assumptions give the relationship between the Authority page and the Hub page: mutual reinforcement, a recursive definition. (Gibson, Kleinberg, & Raghavan [4]).

Fig. 1.



Schematic diagram of Root Set and its derived Base Set

Based on the two points mentioned above, the HITS algorithm is good at extracting and finding better quality web pages in a web system for users' reference. Previous studies have also shown that HITS algorithms are commonly used in recommendation systems to find important topics in them (Y.W. Liu & J.L. Huang [3]). The HITS algorithm has been shown to coincide with this study's attempt to filter out unknown "social impact" authority from many web pages, and it is hoped that this will serve as a reference for future researchers.

The HITS algorithm gives each web page two scores, which are: 1. Authority Score and 2. Hub Score.

The HITS algorithm is as follows. Give the query term q in the search engine, take the first n pages (e.g., n = 200) from the total set of returned result pages as the root set (S), then S meets (Kleinberg [5]).

1. The pages in S are fewer in number.

2. The pages in S are related to query q.

3. The pages in S contain more authority pages.

So far, index-based Web search engines have been the main tool for users to search for information.

However, these search engines are not suitable for many searches in the same domain, especially when the subject of any breadth contains thousands or millions of relevant pages (Chakrabarti et al. [6]). Therefore, how to present the correct and most valuable pages to users becomes an important issue. The HITS algorithm is a graphical algorithm to analyze the importance of web pages.

However, HITS also has obvious drawbacks, such as taking too long and being prone to Topic Drift (Nomura, Oyama, Hayamizu, Ishida, & Japan [7]). In this study, these problems were specially considered and improved, and the detailed experimental methods will be described in Sect. 4.

2.2 Social Impact of ESG

Previous studies have shown that investors consider ESG ratings an additional criterion in addition to a company's bond rating. However, bond ratings are similar for each company, while ESG ratings are significantly divergent (Dimson, Marsh, & Staunton [8]). At the same time, there is no significant return difference between ESG ratings and returns. Other studies have separated ESG into three separate factors and attempted to distinguish which factor is most strongly associated with financial performance (Ahlklo & Lind [9]). However, they both suggest that investors should no longer expect returns by judging by ESG ratings (Halbritter & Dorfleitner [10]). However, these

studies suggest that when selecting two companies, choosing the one with the higher ESG rating is recommended.

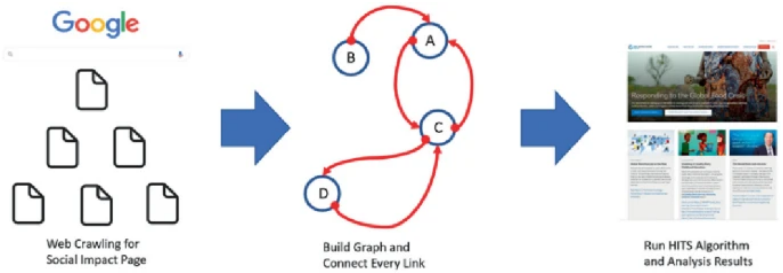
These literature studies show that companies with higher ESG ratings mostly have better fundamentals, representing positive mutual feedback between the company and society. Therefore, ESG is not only an important issue that modern companies must pay attention to but also a key to the long-term operation of the company. However, there is no unified criterion for ESG (Dorfleitner, Halbritter, & Nguyen [11]). The literature above shows that there is no standardized standard for the "S" in ESG. What kind of social contribution is considered good? Is it possible to extract good social standards from some successful companies? In this study, we hope to find out the social impact of ESG by the HITS algorithm from the web pages of many successful companies and provide a reliable standard for subsequent researchers.

3 Research Methodology

This study is divided into three parts, as shown in Fig. 2. In the first stage, web crawlers will be used to collect as many Social Impact related web pages as possible and record all out-links of each web page to build a root collection. In the second stage, all web pages are stored in nodes and added to relationships according to the relationships accessed in the first stage to complete a directed graph containing all web pages. The third stage is

to execute the HITS algorithm by this graph and modify the data or change the score weights to do the final result analysis.

Fig. 2.



The Research Architecture

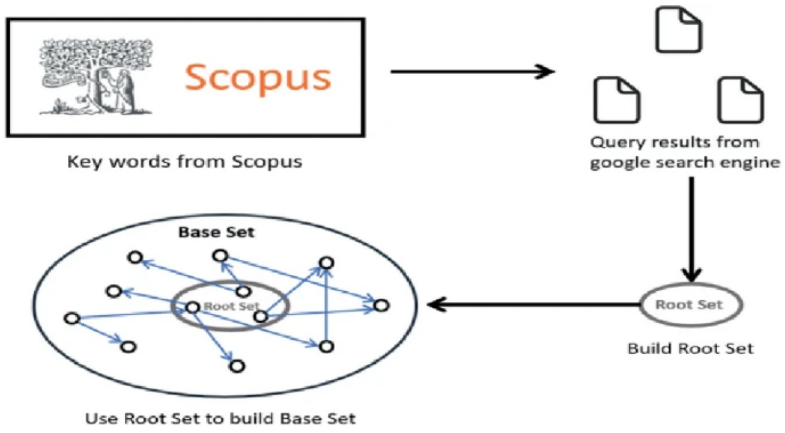
3.1 Research Process

This study uses the HITS algorithm based on the query engine, so it is necessary to start the algorithm from the keyword query, and the keyword collection process is shown in the figure. The first part of this study is to search for papers in different fields using Scopus and retrieve the most repeated keywords as the set of keywords to start the algorithm. The idea of using the most repeated words is inspired by the association rule (Srikant & Agrawal [12]). We believe that the keywords satisfying a certain repetition can be used as the set of keywords to start the algorithm, just like the association rule satisfying the minimum support threshold and the minimum support confidence threshold.

The data collected above is stored in the graph with the data structure as in Fig. 3, so that G = (V, E)

is a directed graph with vertex set V and edge set E, where E is a subset of V × V. For a given vertex Vi, In(Vi) is the set of vertices pointing to it (In-link set), and let Out(Vi) be the vertex pointing to Out-link.

Fig. 3.



Keyword search flow chart

3.2 Algorithms Processing

The algorithm first gives all the nodes in the graph a fixed Hub score, which is initially the same for each node, and the following are the weights of the nodes in the basic update algorithm (1).

1. Updated authority values of all nodes in the graph: for all nodes V, (\({v}_{i}\)) the sum of all In-link(\({v}_{j}\)) of the Hub values \({v}_{j}\in {N}_{in}\left({v}_{i}\right)\).

2. Updated hub values of all nodes in the graph: for all nodes V, (\({v}_{i}\)) the sum of all 0ut-link(\({v}_{i}\)) of the Authority values \({v}_{j}\in {N}_{in}\left({v}_{i}\right)\)

3. Standardized Authority values and Hub values.

4. Repeat points 1, 2, and 3.

5. Terminate the iteration if the maximum number of iterations is reached or the error of change is less than the error tolerance.

$$ \begin{array}{*{20}l} {Authority(v_{i}) = \sum\limits_{{v_{j} \in N_{in} (vi_{{}})}} {hub(v_{j})} } \hfill \\ {hub(v_{i}) = \sum\limits_{{v_{j} \in N_{in} (vi_{{}})}} {Authority(v_{j})} } \hfill \\ \end{array} $$

(1)

This algorithm will be implemented using Python code, using two Dictionary containers to record the node's Authority score and Hub score, respectively, and update each individual node sequentially. The reasons for using Dictionary containers are (1) Python Dictionary is faster to find, and (2) Dictionary features can ensure that nodes will not be duplicated, and it is easier to add nodes dynamically afterward and to optimize the dynamic maintenance process if there is a follow-up.

4 Research Experiment

4.1 Data Collection

The first step is to create a set of keywords. Since this study is a new field of research, there are no keywords related to "social impact" for the root set to be implemented. Therefore, we first use the search engine built into the Scopus paper database

and type in the keywords: 1. “Social Impact”; 2. “Social Value”; 3. “Value Impact”.

A total of 352 papers were queried using the Scopus engine for the above three keywords, and the keywords mentioned in these papers were repeated more than 4 times (50 in total) as the starting query for the HITS algorithm. Each keyword query was processed through a brand new incognito browser to ensure query results are not altered by past query preferences, language, region, or private cookie results. After removing the first page of query results (about 9 results) for each keyword, including the abandoned results due to long response time and the duplicate results, we found that the total number of non-duplicate pages was 384. We used this as the Root Set of the program. Next, according to the web pages of the above root collection, requests were made in turn, and the hyperlinks in all HTML documents were obtained as many as possible from all responses. This section retrieved all < a > tags, and the HTML < a > elements create hyperlinks to external, other pages, files, email addresses, or other URLs.

In this study, a complete crawler and an indexing system were established to crawl tens of millions of data and store more than 3 million non-repetitive website data in total. In order to implement the HITS algorithm, the web crawler needs to crawl all the hyperlinks of the web pages. Although this is a simple task, the search time is huge, and the

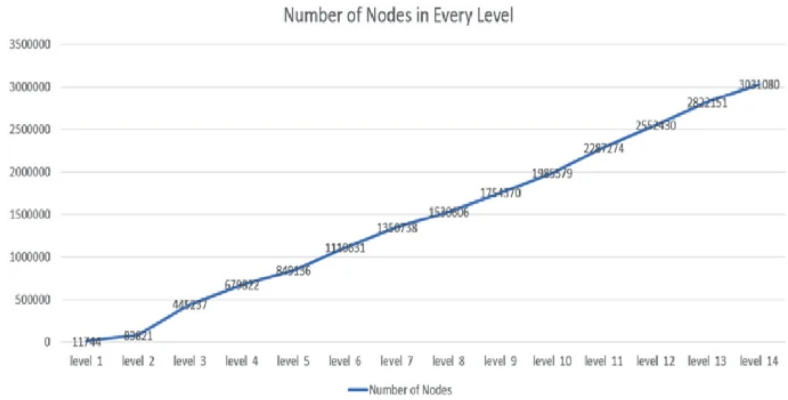
number of pages is very large. In addition, each link in the database needs to be compared, which is another huge amount of time spent (time complexity $O(N^3)$). And this does not include the various bugs web crawlers are bound to encounter. In summary, the whole crawling process is not an easy task. This study has proposed an effective solution, which will be described below.

This study is a hyperlink-oriented algorithm, so only the links starting with HTTP and HTTPS in the <a> tag in the HTML text of the web page were taken. The algorithm was suspended after the search of all websites in each layer, and the number of "non-duplicate pages" added in this layer was counted first. If the number of non-duplicate pages added in this layer is less than 10% of the total number of non-duplicate pages, then we consider that the Base Set is close to convergence. At each level, we have compared the pages in the database to see if there is any duplication. If there are duplicate pages, we delete them, otherwise, we put all non-duplicate sites into the next search level. This was repeated until the algorithm finally reached the convergence condition. In this study, we conducted 14 levels of search, and the rate of increase of non-duplicate new pages was 7.40318289134777%, and the total number of non-duplicate pages was 3031080 before the search was stopped (Fig. 4 and 5).

The following are the descriptive statistics of all the collected web data sets.

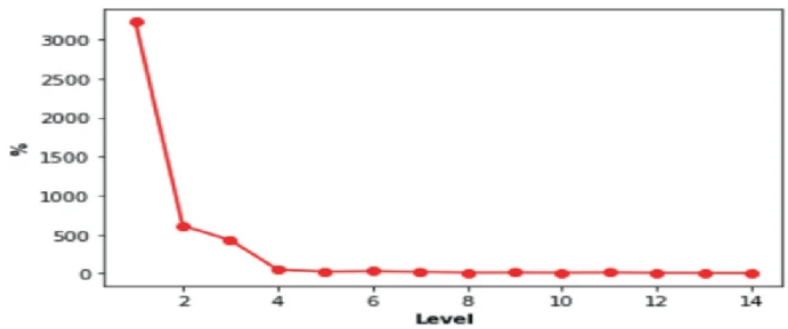
- The average number of Out-links per node = 71.69195092644324.
- Median Out-links per node = 29.
- Number of Out-links per node = 0.
- Maximum number of node out-links = 38400

Fig. 4.



The total number of pages in each layer (no duplicate pages)

Fig. 5.



Percentage increase of non-repeated web pages for each layer (conforms to power distribution)

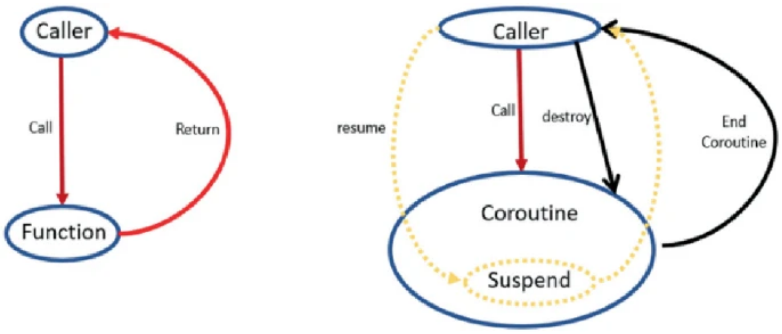
However, the shortcomings of the HITS algorithm have been clearly pointed out in previous studies because it is an algorithm based on search engine query initiation, where the high time cost is the obvious shortcoming of the algorithm (Patel & Patel [13]). The crawling time of several days to weeks greatly reduces the smoothness of the study and is an insurmountable obstacle. This problem was also encountered in the implementation of this study, and because of the huge number of keywords searched in this study (50 in total), the hyperlinks extended from the root set were larger than those of other studies, and the total number of search sites was even close to hundreds of millions. Therefore, it is important to consider how to solve the significant time cost required to start this study.

In this study, the Python Selenium module was used to avoid the detection of the anti-crawler by using its human click simulation function. This is because the anti-crawler not only blocks the data collection in this study but also may cause the whole crawler to stall or have no response. The detection of anti-reptiles by the Selenium module proved to be effective in this study, but the time cost was very high because it simulated human clicks. This study requires crawling tens of millions of data, so the Selenium module approach was not used in this study for the time being.

This section highlights the technique used in this study—Asyncio asynchronous programming for writing crawlers in Python. Python's asyncio module is a standard module for asynchronous frameworks introduced only in python 3.4. Previous research has used similar asynchronous programming logic and effectively optimized its code (Shettar & Shobha [14]).

In asynchronous programming, the programmer can execute a Coroutine by dropping it into the Event Loop (as shown in Fig. 6 below). Throughout the execution of the Event Loop, the Event Loop checks all the Coroutine tasks and classifies them into two categories, (1) the list of executable procedures and (2) the list of completed tasks. When a task has been completed, it will be classified as "Completed Tasks" until all tasks in the Event Loop have been completed (all are classified as Completed Task), then the Event Loop will be terminated.

Fig. 6.



Asynchronous programming Coroutine call principle and differences from general programs

The waiting time required for a typical linear crawler is very long. With such a large amount of crawling data as this study, it took days to tens of days just to crawl the hyperlinked information by waiting for each packet to be sent in turn. In addition, this crawler contains a lot of input/output operations. For such I/O-intensive operations, the linear crawler cannot effectively handle the errors often encountered by crawlers. Finally, this study was a program that encountered a lot of waiting (waiting for packets to come back) because the CPU processor spent a lot of time waiting for network I/O. However, if we directly use preemptive multitasking to split the crawlers in this study, most of the programs would still be waiting due to a large number of waiting for tasks (more than tens of millions of crawlers), and there may still be potential race conditions. Therefore, when executing a large amount of I/O code like this study, this study prefers to use asynchronous programming rather than linear crawlers and multi-execution sequential code programming.

After we wrote the program using Python Asyncio, we reduced the crawling time from tens of days to weeks to half a day (about 15 h), significantly reducing the crawling time.

4.2 Data Preprocessing

Split Info is often used to penalize nodes with too much branching (Harris [15]). We have speculated that this method is similar to the nodal-directed

graph in this study. In the above-mentioned directed graph, if the node has many outward links, its Hub value may be better, affecting the subsequent Authority score. Therefore, this study tries to modify the algorithm by using Split Info (2).

$$ - \sum\limits_{i = 1}^{k} {\frac{{N(v_{i})}}{N}} log_{2} \frac{{N(v_{i})}}{N} $$

(2)

The formula of Split Info is shown above. In this study, *N(vi)* is the number of instances assigned to node *vi,* and *k* is the total amount of splitting. Split Info splits the entropy of a partition into its sub-nodes and evaluates whether the split will produce a large number of sub-nodes of the same size. For example, if each partition has the same number of instances, then *vi: N(vi) /N = 1/k,* and the split information will equal *log2 k*. Therefore, if a node produces many splits, then its Split Info is also large, reducing the gain ratio.

In this study, Split Info was used as a penalty for nodes with too many outbound links, meaning that if a node (web page) has a large number of branches (outbound links), its hub value calculated from the original formula would keep adding up the weights of all outbound links in each iteration to update the weights. By dividing by the Split Info value, we try to restore the values of these nodes to a reasonable range.

Another problem was found in the data processing stage. The collected data mentioned above shows many web pages with the same hyperlinks as the original web pages. The following Fig. 7 shows the data of the duplicate domain.

Fig. 7.

It is found that in the collected data set, some webpages have subpages with the same domain.

This situation was not consistent with the previous assumptions. First, the search for the HITS algorithm was based on the hyperlink between different web pages. However, because the previous HITS algorithm implementation might not be able to focus on so many aspects (such as the 50 keywords in this paper), most of the searches and rankings were conducted in a single field. Most of the searches and rankings were conducted in a single field, so similar social networking sites such as “Amazon,” “Facebook,” “Tumblr,” or the electronic commerce industry were not considered, and such sites usually have a large number of self-directed hyperlinks. Second, HITS pays much attention to the quality of the Root Set; otherwise,

they found a set of websites could easily produce "Topic Drift," and the algorithm cannot determine the valid results from the low-quality data set.

Based on the above two points, this study attempted to leave only "outward" links in the relationship between websites, meaning that all hyperlinks leading to their own domains would be deleted, and the deleted data would be used to create graphs. In this study, we used Regular Expression to capture the domain part of each URL, sorted all the in-links and out-links of each URL in turn, and deleted the URLs with the same domain directly.

In this study, each URL was converted into a unique integer to implement the HITS algorithm, and these integers were used as IDs stored in the graph. After confirming that the nodes in the graph were non-duplicate, we assigned each node an initial Authority score and a Hub score. Usually, all nodes in the graph would start with the same weight, with additional changes described in the following methods.

4.3 Experimental Result and Analysis

A total of three experts were asked to evaluate the results of this study and rank the top 10 web pages analyzed by each of the four methods. Among them, "4" was the most agreed that it represents Social Impact Authority Page. "1" was the most disagreed. "0" was considered irrelevant. The results are shown in the table below.

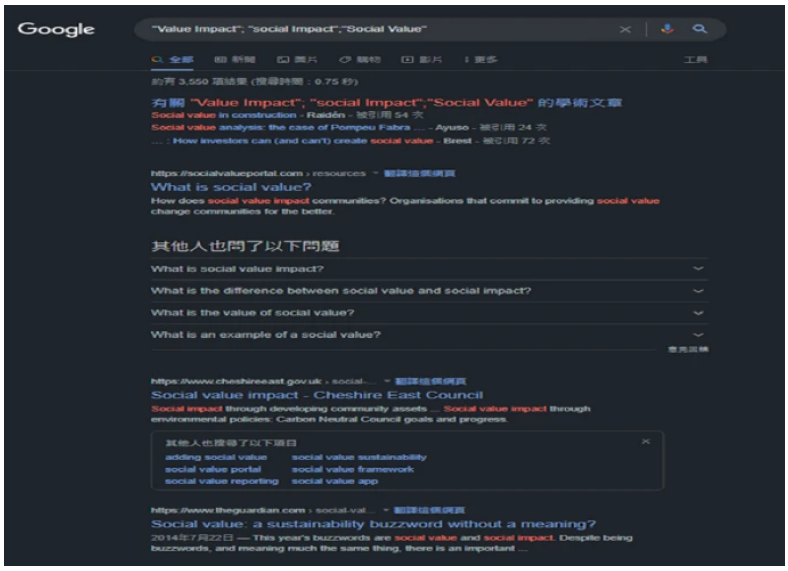
In this study, four types of dispositions were performed on the previously collected datasets, (1) the original HITS algorithm, (2) Split-info was used to calculate the original data, (3) Same Domain Removal, and (4) used Same Domain Removal to process the data before using Split-info to compute. The result showed that the same domain collection was distributed into several regions due to the ranking relationship of the algorithm. In order to make the distribution of the top 10 authoritative web pages clearer, this study took the first web page of different domains as the representative and listed the top 10 authoritative web pages, respectively. The results are presented in Tables 1. The web pages were retrieved on May 20, 2022.

This study used Google Chrome as the browser to support the study results. In addition to being the first search engine to start the algorithm, it is also the most popular browser in the world today. Previous studies have shown that the Google Chrome search engine uses PageRank techniques to help it produce highly accurate results (Brin, Page, & systems [16]). The PageRank algorithm is described in detail in Page, Brin, Motwani, & Winograd [17].

This study verified that the keywords searched in the Scopus database: Social Impact, Value Impact, and Social Value were firstly typed in the untraceable google browser and compared the results of the keywords searched in the browser

with the results of this study. We compared the search results of the keywords on the browser with the search results of this study to find out which was more representative in searching for Social Impact Authority. Figure 8 are the screenshots of the results of the above three keywords, respectively. The results of the Google browser search were used to determine whether the authoritative websites pointed out in this study were better than Google after expert discussion.

Fig. 8.



Screenshot of Google Search “Value Impact”, “social Impact”, “Social Value”

First, experts agreed that the results of individual searches for Social Impact, Value Impact, and Social Value keywords did not represent the authority of Social Impact. Most noun explanations appeared first, and the results lacked a “global” character compared to this study.

Another expert suggested that the study was initiated by typing “Social Impact, Value Impact, and Social Value” into Scopus, and the 50 most frequent keywords were suggested. The search terms were then dropped into a blank Google browser. Therefore, when verifying the merits of authoritative websites, it is necessary to type in all three keywords together to have a fairer judgment. The first result is a link to a related paper, and then Social Value explains the definition of the term, which is not in line with the requirement to find an authoritative website.

The third search result was "Social value impact - Cheshire East Council (https://www.cheshireeast.gov.uk/council_and_democracy/your_council/social-value/social-value-impact.Aspx).“ The experts believe that although it meets the definition of a Social Impact website, it has regional limitations. Compared to this study’s results, the results have a more global perspective and are more representative of Social Impact’s authoritative website.

In general, the first search result given by Google search is mostly “explanation of terms.“ Next, according to the keywords, links to discussion articles were given, or pages that were relatively local or might mention the keywords related to this study, but no authoritative websites with global representation were given. Compared to the results of this study, the web pages recommended by the

Google search engine hardly matched the topics we were seeking.

Table 1 below shows the results of this study using four different methods. The results of the third authoritative website are already biased. "Twoje Drzwi do IT" means "Your Gateway to IT," a website that provides training and online consulting services, which is considered by experts to be very different from the objectives of this study.

Table 1. Total of three experts

The results of the two modified HITS algorithms divided by Split Info were discussed by experts and did not meet the objectives of this study, so they were not used.

However, Table 2 gives a fairer result. After expert discussion and comparison with the above Google results, the results of Table 2, "Same Domain Removal," best meet the criteria of "Global Social Impact Authority." Because the ranking results such as World Bank, MIGA, IFC, WHO, etc., have a global scope of business and do not focus on a single region or rank high because of relevant keywords, it is more authoritative and representative website compared to other results.

Table 2. HITS algorithm result after processing with Same Domain Removal

method

5 Conclusion and Future Research

This study aims to determine the authority of social impact web pages by collecting a large number of social impact related web pages from the World Wide Web, modifying them with this graph, and then using the HITS algorithm to find out the authority of social impact web pages.

The contribution of this study can be summarized in two points.

1. The asynchronous crawler program adopted in this study can greatly reduce the crawler execution time compared to the original linear crawler, which saves a lot of time for the HITS algorithm to start.

2. Compared with the original algorithm, the HITS—Same Domain Removal method results in 10 web pages that can best represent the social impact.

This study used asynchronous programming to significantly shorten the crawler program time from tens of days to one day. We also found the top 10 social impact authority pages, which many experts and scholars confirmed, and have more global and oriented viewpoints than google search and more explanatory power.

In addition, this study also tried other additional methods to compare with each other. Compared with the previous study, this study can now search the keywords of the possible domain quickly, and the modified HITS algorithm is better than the original algorithm. The modified HITS algorithm can better search for the authority of the topic than the original algorithm.

The limitation of this study is that only English language web pages are extracted in principle, and the analysis ability of web pages in other languages may not be so comprehensive.

This study tried to reduce the score weight of web pages with many branches by using the Split Info method, which is well-intentioned but may be overly penalized by using Split Info, and it is suggested that subsequent researchers can work in this direction.

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Author information

Authors and Affiliations

Department of Business Administration, National Central University, No. 300, Jhongda Road, Jhongli, Taoyuan, 32001, Taiwan (R.O.C.)

Yang Ruei Jheng, Ping-Yu Hsu, Jiu Zhong Chen & Yu-Chun Chen

Department of Industrial Engineering and Management, Ming Chi University of Technology, No. 84, Gongzhuan Road, Taishan, New Taipei, 24301, Taiwan (R.O.C.)

Ming Shien Cheng

Corresponding author

Correspondence to Ming Shien Cheng .

Editor information

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