



Available online at www.sciencedirect.com

ScienceDirect



Procedia - Social and Behavioral Sciences 226 (2016) 27 - 34

29th World Congress International Project Management Association (IPMA) 2015, IPMA WC 2015, 28-30 September – 1 October 2015, Westin Playa Bonita, Panama

Predicting the future of project management research

Uchitpe, Matthewa, Uddin, Shahadata,*, Crawford, Lynna

^aFaculty of Engineering & IT, The University of Sydney, Darlington, NSW 2008, Australia

Abstract

Although there has been much recent research on Project Management (PM), this research field is still relatively very young with many aspects still to be uncovered. Studies of the present literature have documented that, as no surprise, new research topics and emerging knowledge domains within this research field continue to appear at a rapid pace. This study aims to predict, based on a quantitative approach, the potential research areas that could appear in the foreseeable future of PM research. As carriers of PM knowledge entities, this study utilised different keywords that had been extracted from all publications of a reputed PM journal over a period of five years (i.e. 2009-2013). By applying the quantitative approach on this research dataset, this study made a projection about the future potential PM research topics. This projection will bring a competitive advantage to PM stakeholders by choosing a suitable field for investment, help aspiring PM researchers to choose a promising topic, and guide PM funding agencies as well as policy makers in distributing available research funds.

 $@\ 2016\ The\ Authors.\ Published\ by\ Elsevier\ Ltd.\ This\ is\ an\ open\ access\ article\ under\ the\ CC\ BY-NC-ND\ license\ (http://creativecommons.org/licenses/by-nc-nd/4.0/).$

Peer-review under responsibility of the organizing committee of IPMA WC 2015.

Keywords: Project management research; knowledge entity; growth analysis; z-score; and prediction.

1. Introduction

The art of Project Management has been in practice for thousands of years, with one of the earliest instances seen in the construction of the Great Pyramid of Giza circa 2570 BC (Mavenlink, 2012). However, only within the past century has it officially become an internationally recognised professional field, a respected knowledge domain, a structured doctrine, and an institution. With the 'Modern Project Management' era starting in the middle of the 20th century (Weaver, 2007), the field is still relatively very young with lots of aspects still to be uncovered. It then

* Shahadat, Uddin. Tel.: +61 2 9351 2118; fax: +61 2 9662 6566. *E-mail address:* shahadat.uddin@sydney.edu.au

1877-0428 © 2016 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Peer-review under responsibility of the organizing committee of IPMA WC 2015. doi:10.1016/j.sbspro.2016.06.158

comes as no surprise that new research topics and emerging knowledge domains within the Project Management field continue to appear at a rapid pace. Thus, there has been plenty of recent research and numerous studies on trends and patterns surrounding emerging knowledge areas, specifically in the Project Management field.

The aim of this study, in particular, is to formulate a means of predicting potential areas of research or emerging knowledge that could arise in the foreseeable future, using two types of journal keywords and unique analysis of these keywords. With preceding studies demonstrating similar fundamental intentions and even overlapping methods, such as identifying emerging trends and passing fads (Pollack & Adler, 2015) and uncovering trends in Project Management within a particular timeframe (Crawford, Pollack, & England, 2006), such studies mostly give insight into the current or past state of the Project Management domain, via varying means. However, the power to predict upcoming research topics, as set out in this study, could benefit many stakeholders (Reiss, Vignola-Gagné, & Kukk, 2013), especially in industries such as Medicine, Health, Finance, and Project Management, where ongoing research continues to be conducted in pursuit of newer technologies and broader horizons. With informed foresight, research funding could be better directed towards emerging fields, research results could be yielded more rapidly, technology could be advanced faster than ever before, newer medicines and cures to currently incurable diseases could be uncovered, future research topics could be researched sooner, diseases could be predicted given an individual's medical history, and organisations from any industry could use such insights to gain a competitive advantage by predicting the future market (Guo, Weingart, & Börner, 2011).

The idea for this study was inspired by preceding studies such as Kleinberg's (2002) burst detection algorithm, which demonstrated that sudden bursts or declines in occurrence of words used within the article indicate either the unearthing of a new knowledge domain, or its collapse. Using this premise, the growth, frequency, and dynamics of journal keywords are analysed by applying statistical methods. The z-score gives rise to a probabilistic indicator, or a sign of significance of a keyword's trend in growth or decline and hence, the growth of a new topic (Uddin, Khan, & Baur, 2015). Thus, the proposed model in this paper will explain how journal keywords and statistical analysis can be manipulated to calculate the likelihood of new knowledge emerging, firstly for the Project Management domain, and then eventually all other fields of study or research.

Being able to predict the future for Project Management field is very encouraging at this point in time, where this young field is currently growing and is becoming vitally integrated into every aspect of every industry. No modern organisation can survive without implementing projects, and no project can succeed without an experienced project manager (Coelho, 2012). Any capable project manager must be well equipped with and utilise the right tools, appropriate to the context, in order to successfully guide a project to success. Being informed of future directions will better prepare project managers to know which tools need to be learnt and applied, and in taking apposite steps to resolving expected complications before they become a major concern. Researchers will also be able to identify fruitful new directions for their research.

2. Literature Review

Preceding researchers have proposed various methods and approaches to detecting emerging research topics for different purposes. These methods range from bibliometric including Price's Index (Khan, Choudhury, Uddin, Hossain, & Baur, 2016; Moed, 2005), the impact factor and the immediacy index (Tomer, 1986), to hybrid clustering techniques, text-mining and more recently, hybrid methods (Guo et al., 2011). However, the majority of earlier studies rely mostly on the study and analysis of paper or journal citation information, and if applicable, trends or citation networks (Abbasi, Hossain, Uddin, & Rasmussen, 2011; Uddin, Hossain, Abbasi, & Rasmussen, 2012; Uddin, Hossain, & Rasmussen, 2013). There has also been former research involving the study and analysis of keywords (Julien Pollack, 2015), just like the nature of this very study. The use of keyword clusters had previously been used to predict a website's traffic and was demonstrated to be beneficial to website owners and advertisement agencies, in terms of their business' financial viability (Regelson & Fain, 2006).

Furthermore, Bredillet (Bredillet, 2006a) contributed to the understanding of the future of Project Management via several approaches whilst his intentions were also well aligned to the intention of this study. His work in providing insight into the future of Project Management included several instances of mapping the fields dynamics (Bredillet, 2006b) (Bredillet, 2009), and utilising what he referred to as the co-word approach (Bredillet, 2006c).

On the other hand, methods not so similar have been used on the social media scene, but still recognising and using the power of keywords. Keywords (profile entries) are used to map out social networks (Abbasi et al., 2011) for further study and analysis and while the method itself is not relevant to the paper, it reinforces the fact that

keywords potentially hold considerable information and power. Further evidence for the power of keywords is highlighted through studies which involved classifying keywords for predictive purposes (Ma, 2013). One study that recognised and captured the essence of the dynamism of keywords also happened to be on the social media scene, where the study of evolving keywords was utilised to detect emerging topics and this provided a means of understanding and predicting user behaviour (Chen, Amiri, Li, & Chua, 2013).

There are many fields which require, or would benefit from, the predictive power given by the countless models proposed by previous researchers, as evident in each of the papers aforementioned. The scientific, marketing, economic, engineering, project management, medicine, and health industries are all currently benefiting, but could also profit more with the advancement and improvement of predictive models. By incorporating the notions presented in these previous studies, the model proposed in this paper is inspired by past research and study.

3. Method

This section of the paper describes how the two sets of journal keywords are acquired, revised, filtered, selected, and how their frequency, growth, and significance in growth are calculated. The predictive model that is described here will be referred to as the 'Relative Growth – Probability of Occurrence' model, or abbreviated as RGPOC.

3.1 Relative Growth – Probability of Occurrence Model

The Relative Growth – Probability of Occurrence model proposes a new approach to identifying emerging research areas and knowledge domains. The premise of this model lies upon these four foundational statements;

- (a) Word bursts indicate increasing usage of a keyword and hence, its relative frequency of occurrence.
- (b) Increasing *relative frequency* of occurrence indicates growth.
- (c) Higher relative frequencies imply higher mean growth and z-score.
- (d) Keyword growth is normalised and all data is in relation to the mean of all growths.

By normalising the growth of all keywords, an indication of how significant the growth of a particular keyword is can be attained relative to the mean value of growth. See Fig. 1 below for a graphical explanation. An important criterion for this model is that the keyword must not only have high growth but also show considerable frequency.

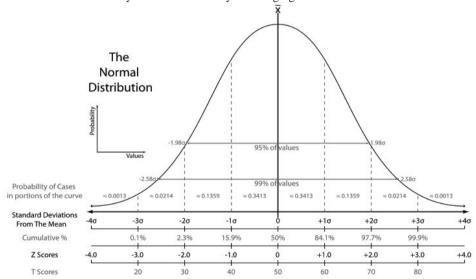


Fig. 1. The normal distribution curve – growth values tend to group towards the mean value, meaning the growth values in the top 5% have some significance.

3.2 Data Acquisition and Preparation

All papers were obtained from the Scopus database and the search results were limited to articles published in the International Journal of Project Management (2009-2013) only. Using the title, abstract, and keyword query *Project Management*, a total of 31,877 results were returned from the Scopus database between 2009 and 2013 inclusively. However, limiting results to articles found only in the International Journal of Project Management (IJPM) returned 410 results. The data were separated into separate Excel documents by year of publication and then converted into .xls format, each article containing information including; title, abstract, authors, year, source title, volume, issue, citation count, link, affiliations, authors with affiliations, author keywords, index keywords, references, DOI, language, and ISSN.

Using Knime, each year's dataset was imported and then processed by:

- Selecting only the title and abstract columns and filtering out remaining redundant information.
- Converting specified columns containing strings, used as title and abstract, into documents.
- Reading and processing the abstract (with Knime) and filtering all punctuations and numbers out.
- Filtering all stop words out of the abstract. The stop word list in-built into Knime contains a list of specified words which is to be detected and removed.
- Having remaining filtered list of words POS (Part of Speech) tagged. This detects the nature of the word and attaches the description to the word.

This process is then repeated for author keywords, which are given. Therefore, not much processing was required. The correct field was only needed to be identified and extracted. Once this was completed, the abstract and author keywords were separated into their respective documents and further sorted by their year of publication. At this stage of the study, there were over 1000 keywords remaining on each list.

Table 1. Description of dataset in numbers

	2009	2010	2011	2012	2013
No. of Articles	75	74	88	80	93
Keyword/Paper					
Author Defined	3.01	3.05	2.57	2.83	2.43
Knime Defined	5.81	5.89	4.95	5.45	4.69

Complete, separate lists of abstract and author keywords from every year were compiled. Then plurals and duplicates, both identical and words which were the same but had a mismatch in upper or lower casing, were removed using Excel. The next cut involved manually filtering words which had a zero occurrence in the 5 year interval. Having a zero occurrence would imply that the word was not relevant enough to be considered during that 5 year period. An observation which was consistent with this action was that words that had a zero occurrence within the 5 year period had low, or zero, occurrences in adjacent years as well. Same words in different tenses and words that carried the same meaning or were very similar were also cut. Only the word with the higher occurrence would be retained. The final manual cut involved cutting any symbols or numbers which were unsuccessfully filtered by Knime, and words which carried no substance (e.g. conjunctions and personal pronouns). The basic keyword statistics after these cuts is given in Table 1.

3.3 Frequency Analysis

The frequency analysis, which was undertaken and expressed over a span of five years, gives an indication of the keyword's occurrence as a fraction, or percentage, of the total number of journals analysed. For example, one particular keyword occurs in 50 different scientific journal papers of a particular research domain, over a span of ten years. If 500 scientific journal papers are published within the same period, the relative frequency of this particular keyword is 50/500 = 0.1 (or 10%). A higher fraction (relative frequency) would represent a greater use of that keyword amongst the research community.

The frequency analysis involves two stages: totaling the frequency of every word on the final keyword list appearing in the abstract of each paper for every year and expressing that frequency in terms of a percentage (relative frequency) relative to the total number of papers published in that particular year. The list of keywords was sorted in decreasing order by their respective frequency, and coincidentally by relative frequency counts as well. The number of keywords on this list that would make the final cut was dependent on the results of the growth analysis, which will be explained in the subsequent section.

3.4 Growth Analysis

Unlike the frequency analysis, the growth of a keyword represents the dynamics of a keyword over the *total* span of the period considered. This analysis can point out sudden progression or decline of keywords, giving some indication of possible discoveries or failure of particular knowledge domains. The growth analysis involves the application of Equation I (Uddin et al., 2015) below to the results of the frequency analysis, by finding the percentage difference between the frequencies of a keyword for two consecutive years. For example, Equation I below can be applied to the frequencies of a keyword in 2009 and 2010 to quantify the growth for that period.

Growth=
$$\sum_{i=1}^{n-1} \frac{(g_{i+1} - g_i)}{g_i} \times 100\%$$
 (1)

Where, the frequency of a keyword in 2010 and 2009 are denoted by g_{i+1} and g_i , respectively. Four growth values were calculated for every keyword in both datasets, for each consecutive time interval (2009-2010, 2010-2011, 2011-2012, 2012-2013), and the mean and standard deviation of the growth of all keywords were determined.

3.5 Normalising Data and Applying the z-score Method

By applying the z-score formula, Equation II, below, the results of the growth analysis become normalised. The z-score analysis involves using the frequency of keywords to develop a frequency distribution graph, and calculating the mean and standard deviation of the graph. The z-score test utilises these parameters via Equation II, giving each keyword a standardised score by which it can be compared to other keywords. The distributions of results are then translated into standard normal distribution (normalised), where the mean is 0 and standard deviation is 1.

$$z = \frac{X - \bar{X}}{s} \tag{2}$$

Z-score gives an indication as to how far away the frequency of a particular keyword is from the average frequency of all the keywords. X represents the growth of a particular keyword, \bar{x} represents the mean growth of all keywords, and s represents the standard deviation of the growth of all keywords. Keywords that show an abnormally high or low frequency will have a z-score indicating that the keyword's frequency is in the top or bottom 5% (corresponding to a significance factor of 0.05 or less, or 0.95 or more). Figure 1 illustrates this concept well, where most keywords have a frequency close to the middle of the graph and keywords with higher or lower frequencies are not as common. By sorting the keywords by their significance factor, the keywords with significance factors of less than or equal to 0.05 were considered. These keywords had frequencies that were part of the top 5% of all keywords, demonstrating that there has been a very high increase in frequency of thos

4. Results

Table 2 below contains information regarding the frequencies and relative frequencies of the 10 top recurring and relevant Knime-derived keywords.

Keywords	Frequency (Relative Frequency in percentage)						
	2009	2010	2011	2012	2013		
PM	73 (97%)	67 (91%)	46 (52%)	39 (49%)	61 (66%)		
IPMA	73 (97%)	66 (89%)	45 (51%)	36 (45%)	54 (58%)		
Era	46 (61%)	43 (58%)	47 (53%)	39 (49%)	55 (59%)		
Paper	46 (61%)	42 (57%)	44 (50%)	28 (35%)	40 (43%)		
Develop	33 (44%)	30 (41%)	38 (43%)	31 (39%)	45 (48%)		
Rate	35 (47%)	26 (35%)	32 (36%)	32 (40%)	44 (47%)		
Art	30 (40%)	29 (39%)	37 (42%)	25 (31%)	38 (41%)		
Actor	30 (40%)	22 (30%)	29 (33%)	18 (23%)	35 (38%)		
Mode	17 (23%)	23 (31%)	29 (33%)	28 (35%)	31 (33%)		
Sent	25 (33%)	23 (31%)	28 (32%)	16 (20%)	31 (33%)		

Table 2. Top 10 Knime-derived abstract keywords according to highest frequencies (2009-2013)

Table 3 below contains the results of the growth analysis study. The keywords are sorted by their z-scores and significance scores, ranking keywords in order of notable growth.

Table 3. Author-defined (AD)/Knime-derived (KD) abstract keywords with growth significance of 0.05 or below

AD Keywords	Growth	z-score	Significance	KD Keywords	Growth	z-score	Significance
Portfolio	208.04	5.11	0.00	Contractors	142.67	3.94	0.00
Enable	172.12	4.10	0.00	Culture	136.45	3.74	0.00
Similar	164.82	3.90	0.00	Learn	125.05	3.36	0.00
Position	164.04	3.87	0.00	Choice	122.91	3.29	0.00
Solutions	156.14	3.65	0.00	Engineer	114.07	3.00	0.00
Positive	149.80	3.47	0.00	Probability	105.10	2.70	0.01
Culture	136.45	3.10	0.00	Portfolio	101.15	2.57	0.01
Practitioner	133.50	3.02	0.00	Networks	101.06	2.57	0.01
Contractors	132.65	2.99	0.00	Theoretical	93.60	2.32	0.03
Empirically	121.97	2.69	0.01	Practitioner	87.51	2.12	0.04
Engineer	114.07	2.47	0.02	Building	84.31	2.02	0.05
History	110.17	2.36	0.02	Ü			
Probability	105.10	2.22	0.03				
Building	99.73	2.07	0.05				
Tender	98.62	2.04	0.05				

From Table 3, the keywords from *portfolio* to *empirically* all have significance between 0.00 and 0.01. This signifies that the growth of these particular Knime-defined keywords are in the top 1% of all Knime-defined keywords, deeming the growth of these keywords worth considering as 'burst' in frequency. The keywords from *contractors* to *networks* in Table 3 (for KD keywords) have significance between 0.00 and 0.01, indicating a possible 'burst' in frequency.

Table 4 below conveys identical information to Table 2, but for author-selected keywords.

Table 4. Top 10 author-selected keywords showing the highest frequencies

Keywords	Frequency (Relative Frequency in percentage)						
	2009	2010	2011	2012	2013		
PM	74 (99%)	67 (91%)	57 (65%)	42 (53%)	61 (66%)		
Manage	47 (63%)	51 (69%)	64 (73%)	51 (64%)	66 (71%)		
Rate	36 (48%)	26 (35%)	41 (47%)	41 (51%)	44 (47%)		
Art	31 (41%)	29 (39%)	42 (48%)	32 (40%)	38 (41%)		
Result	33 (44%)	26 (35%)	34 (39%)	29 (36%)	35 (38%)		
Based	22 (29%)	16 (22%)	30 (34%)	28 (35%)	36 (39%)		
Ties	27 (36%)	22 (30%)	24 (27%)	29 (36%)	29 (31%)		
Construct	28 (37%)	21 (28%)	33 (38%)	21 (26%)	26 (28%)		
Model	15 (20%)	19 (26%)	29 (33%)	29 (36%)	28 (30%)		
Manager	18 (24%)	19 (26%)	32 (36%)	15 (19%)	30 (32%)		

As verified in Tables 2 and 4, the keyword *PM* took the first position for both categories of keyword (i.e. author-selected and Knime defined), whereas keywords such as *manager*, *rate*, and *art*, retained their positions in the top 10 recurring keywords from 2009 to 2013.

The *z-score* column in Table 3 contains the z-score of each keyword, which was obtained using the formula mentioned in section 3D. This z-score is vital in obtaining the 'significance factor', which used the z-scores to normalise the data and give meaning to the frequency of each keyword. As aforementioned, a significance factor of 0.05 or less, or 0.95 or more, means that the frequency of the keyword is abnormally high or low respectively, and indicates that these keywords are worth considering as 'word bursts'. Table 3 has been tailored to display only keywords which have a significance factor of 0.05 or less (there are no keywords with a significance factor of \geq 0.95.

One instance of a keyword which shows consistent and strong growth is *culture*, ranking 7th and 2nd overall, for the Knime-defined and author-selected categories respectively. This could imply that things surrounding the notion of *culture* had possibly grown to become an emerging topic of interest within the 2009-2013 periods. This may have seen the notion of organisational culture becoming a growing influence in the domain of project management, from 2014 to current. Hence, this implication of the results can be seen with regards to its predictive applicability, indicating that *culture* and its influence on project management should be researched further. Words which show

overlap include culture, portfolio, practitioner and probability. These words appear in both keyword lists, reaffirming growth in the keywords' usage.

5. Discussion and Conclusion

This paper describes a new proposed model, Relative Growth – Probability of Occurrence, which aims to predict emerging topics in Project Management by studying the dynamics of keywords. Words that showed a significant growth rate and frequency indicated a possible emerging topic.

The reason why keywords are chosen as the main focus of analysis is because they carry substantial information surrounding the core concepts of papers, to a very concise degree (single words for this study). No other characteristic of a journal can be attributed the same power when describing the essence of a journal in only a word or two, including the journal title, author, date of publication and abstract. By analysing the dynamics of simple, single word, /elements of an entire journal paper, the crux of it can be extracted and the relevance of the entire paper can quickly be determined. In essence, an upsurge or depletion in frequency of a keyword is likely to indicate a growth or attenuation of interest, in any field that could be described by that particular keyword.

It is understood by Mane and Borner (2004) that the driver behind the word bursts is a wider scope of usage for particular words. This often led to new research trends and, hence, new topics and knowledge domains emerging, especially through their research in the biomedical field. It is observable in the results of this study that an increase in relative frequency of a keyword is correlated to the total growth of the keyword, explaining why these trends can be observed in the results of this study.

A general observation, which can be made from the results of both categories of keywords, is that the keywords with the most significant growth cannot be found in the top 20 most frequently occurring keywords list. This firmly establishes the difference between the implications of abnormally high, frequently appearing keywords, and the significant growth of a keyword. The main focus in this study is not on the frequently occurring keywords, but rather keywords that show the most growth, enough to be included in the top 5% of all keywords. The frequency analysis is included as part of the results as it is a step to obtaining the results of the growth analysis, namely via obtaining the relative frequencies of keywords.

It must be noted, however, that the results of this study are confined to the boundaries of the dataset, which inherently contains limitations. Firstly, only one journal was considered (International Journal of Project Management, IJPM). This poses an issue as the papers included in the journal may be limited by certain criteria. That is, the papers that have been chosen to be included in the IJPM may have been selected because they address one specific issue or subject only. The papers included in a journal are likely to be restricted by certain requirements, authors, publication agencies and so forth, which means the results of this study would also be bounded by these limitations. It is ideal that the journals considered should cover different aspects of project management, so that the results would reflect more accurately on the state of the entire domain. Second, the study covered a short span of 5 years. As can be observed from Tables 1 and 3 in the Results section, the results over the five years for each category of defined keywords are extremely similar, to the extent that the majority of the top 10 recurring keywords are somewhat repeated for both categories. Although the focus is not entirely on the frequency analysis, extremely similar top 10 lists does not indicate strong changes in keyword usage, and, hence, emergence of new knowledge areas. Finally, as outlined in the Introduction and Literature Review sections previous studies with similar intentions and even similar methods have been undertaken. However, this paper contributes a unique approach using qualitative (the information carried by keywords), quantitative (frequency and growth analyses), and statistical methods (z-score method) for the specific purpose of predicting emerging trends for future research.

However, it is evident that this study does not provide a 100% watertight method for predicting the future of Project Management Research. It is most definitely a strong foundation upon which others can conduct further studies. There are still refinements to the process to be made, wider-scoped datasets to be considered, other fields in which to test the model, accuracy over many repetitions to be tested, other types of keywords to considered (index keywords are a valid keyword database), or any other necessary changes. The model was devised with the intent that it could work for anyone, in any industry, even if the results of this study are specifically for the Project Management domain (more specifically the IJPM). In time, it is expected that the proposed method will eventually be expanded upon to improve its accuracy and reliability. Implementing further accepted statistical methods such as time regression series, in conjunction with this algorithm, could improve its predictive power and even possibly produce extra capacities, results and dimensions to the model.

This study certainly indicates a bright future for researchers and the industry in general. The power to predict future topics or knowledge domains can provide stakeholders with strong advantages if used strategically. Considering the results that could emerge and the power it has to potentially revolutionise the research industry, it is most definitely worth investing time and further research into this proposed and other similar models.

References

- Abbasi, A., Hossain, L., Uddin, S., & Rasmussen, K. J. R. (2011). Evolutionary dynamics of scientific collaboration networks: multi-levels and cross-time analysis. *Scientometrics*, 89(2), 687-710.
- Bredillet, C. (2006a). The future of project management: mapping the dynamics of project management field in action. Global Project Management Handbook: Planning, Organizing and Controlling International Projects, Second Edition: Planning, Organizing, and Controlling International Projects.
- Bredillet, C. (2006b). The future of project management: mapping the dynamics of project management field in action. Global Project

 Management Handbook: Planning, Organizing and Controlling International Projects, Second Edition: Planning, Organizing, and
 Controlling International Projects.
- Bredillet, C. (2006c). Investigating the future of project management: a co-word analysis approach. *International Research Network for Organizing by Projects-IRNOP 7*, 24(2), 175-184.
- Bredillet, C. (2009). Mapping the dynamics of the project management field: Project management in action (part 2). *Project Management Journa*, 40(2), 2-6.
- Chen, Y., Amiri, H., Li, Z., & Chua, T.-S. (2013). Emerging topic detection for organizations from microblogs. Paper presented at the Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval, Dublin, Ireland.
- Coelho, L. S. (2012). Why Organizations Need Project Management. Retrieved 18/02/2015, 2015, from http://blog.projectplace.com/why-organizations-need-project-management/
- Crawford, L., Pollack, J., & England, D. (2006). Uncovering the trends in project management: Journal emphases over the last 10 years. International Journal of Project Management, 24(2), 175-184.
- Guo, H., Weingart, S., & Börner, K. (2011). Mixed-indicators model for identifying emerging research areas. Scientometrics, 89(1), 421-435.
 Julien Pollack, D. A. (2015). Emergent trends and passing fads in project management research: A scientometric analysis of changes in the field.
 International Journal of Project Management, 33(1), 236-248.
- Ketan K. Mane, K. B. (2004). Mapping topics and topic bursts in PNAS. PNAS, 101.
- Khan, A., Choudhury, N., Uddin, S., Hossain, L., & Baur, L. (2016). Longitudinal trends in global obesity research and collaboration: a review using bibliometric metadata. *Obesity Reviews*, 17(4), 377-385.
- Kleingberg, J. (2002). Bursty and hierarchical structure in streams. *Proceedings of the Eighth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*(91-101).
- Ma, Z., Sun, A. and Cong, G. (2013). On predicting the popularity of newly emerging hashtags in Twitter. *Journal of the American Society for Information Science and Technology*, 64(7), 1399-1410.
- Mavenlink. (2012, 11/10/2012). A Brief History of Project Management. Retrieved 13/02/2015, 2015, from http://blog.mavenlink.com/a-brief-history-of-project-management
- Moed, H. F. (2005). Bibliometric measurement of research performance and Price's theory of differences among the sciences. *Scientometrics*, 15(5-6), 473-483.
- Pollack, J., & Adler, D. (2015). Emergent trends and passing fads in project management research: A scientometric analysis of changes in the field. *International Journal of Project Management*, 33(1), 236-248.
- Regelson, M., & Fain, D. (2006). *Predicting click-through rate using keyword clusters*. Paper presented at the Proceedings of the Second Workshop on Sponsored Search Auctions.
- Reiss, T., Vignola-Gagné, E., & Kukk, P. (2013). ERACEP Emerging Research Areas and their Coverage by ERC-supported Projects: European Research Council.
- Tomer, C. (1986). A statistical assessment of two measures of citation: The impact factor and the immediacy index. Elsevier, 22(3), 251-258.
- Uddin, S., Hossain, L., Abbasi, A., & Rasmussen, K. (2012). Trend and efficiency analysis of co-authorship network. *Scientometrics*, 90(2), 687-699.
- Uddin, S., Hossain, L., & Rasmussen, K. (2013). Network Effects on Scientific Collaborations. PloS one, 8(2), e57546.
- Uddin, S., Khan, A., & Baur, L. A. (2015). A Framework to Explore the Knowledge Structure of Multidisciplinary Research Fields. *PloS one*, 10(4), e0123537. doi: 10.1371/journal.pone.0123537
- Weaver, P. (2007). A Brief History of Project Management. APM Project, 19(11).