COPENHAGEN BUSINESS SCHOOL
M.Sc. in Economics and Business Administration - Strategy, Organisation and Leadership

Master Thesis

BIG DATA IN SOCIAL SCIENCES

An attempt at proving the existence of leadership and management fashions with big data and quantitative methods.

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Abstract

We apply big data mining and analytic technologies to the study of leadership fashions in order to investigate how such technologies can transform research methodologies in the field of leadership and management studies. We review dominant theories about leadership and management fashions, and the limited manual and bibliometric research methods that scholars have used to investigate them. By contrast, we employ robotic process automation to collect 160 million data points indicating word usage connected to leadership within academic research (Academia), leadership development firms (Business) and the leadership offerings of triple-accredited business schools (Education) between 2008 and 2018. We employ NMDS plots and word cluster analysis to search for patterns and themes that would indicate the diffusion of leadership fashions across these three contexts. Our analysis points to a moderate fashion effect within academic leadership research over the ten year period, but finds no conclusive effect within Business or Education circles. Neither does our analysis indicate any diffusion of leadership fashions across these contexts, and therefore does not confirm the contention in previous research that academics play a key role as management or leadership fashion setters. The results of our analysis do not rule out the possible role of academics as fashion setters, or the existence of leadership or management fashions altogether. But they do call into question the ways that researchers have studied these topics previously, and they challenge scholars to adopt new methods for digging deeper into these topics in the future. We conclude that big data technologies can help make leadership and management research more relevant by drawing on more direct forms of data in exponentially greater quantities, and in the instance of our case study, by providing scholars with a more realistic perspective on their own role and influence over the diffusion of leadership and management fashions and ideas.

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We wish to thank all the people that helped us in one of many ways during the process of writing this thesis.

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Table of Contents

List of Figures and Tables

Chapter 1: Introduction

In this study, we introduce and apply big data mining and analytic methods to leadership fashion research in order to show how we can hereby change the currently applied research methods within leadership and management studies and offer a vantage point into the future development of these domains. After reviewing the existing literature on leadership and management fashions and the limitations that manual and citation-based bibliometric research methods pose, we showcase a set of next-generation tools for this kind of research that are made possible by the recent advances in robotic process automation (RPA) for data gathering and big data analytics for deriving a meaning from the data.

With the support of RPA, we gathered a total of 160 million data points in the domain of leadership research (Academia), leadership development companies (Business) and the leadership offerings of triple-accredited business schools (Education) around the globe. The use of RPA for gathering data facilitates extending the scope of our analysis and also the reach of the data that we gather. The data that we have gathered covers all geographic regions around the world and constitutes aggregate subsets for Academia, Business and Education that are large enough to be already representative on their own. To deduct meaning and draw conclusions from the very large amount of data we gathered, we employed big data analytical methods suitable for the analysis of datasets of this size. Many previously used methods cannot handle such large amounts of data and are therefore insufficient to boil such large quantities of information down into manageable information. Our data analysis centred around the use of NMDS plots and word cluster analysis to search for patterns and themes and to identify variation patterns that could constitute fashions. Then we tracked these patterns to search for any indication of the diffusion of these leadership fashions across academic, business and educational contexts. It is our combination of RPA for the data gathering and the application of the required big data analytical methods to derive meaning from the gathered information that offers a new perspective for the study of leadership and management fashions and lays the foundation for further research of this type.

We aim to shed more light onto the dynamics and diffusion of leadership and management fashion domain by selecting different focus areas for this study. Firstly, we attempt to answer with our research the question if leadership and management fashions exist or not. This is the at very core of this study because it will impact what future research in this area will look like. If we find that leadership and management fashions exist, then we want to know where they exist, meaning if they both exist in leadership and management or if they only exist in only one of these domains.

Setting out to establish the existence of either leadership or management fashions, we wanted to see in more detail how fashions develop and diffuse across Academia, Business and Education in order to identify which actor or set of actors might play a dominant role in setting a leadership and/or management fashion. Identifying diffusion patterns and fashion setters is a strongly intertwined aspect of this study, because only if we find conclusive diffusion patterns, we can with certainty say who acts as fashion setter(s). We thought it would be interesting to see if there is only one or multiple fashion setters and in which context these actors are anchored (Academia, Business or Education).

Lastly, in our preliminary research of the topic, we are unable to find any scholars offering quantitative proof for the existence of leadership and management fashions. Therefore, our study aims at finding exactly this quantitative proof with the help of big data and show the usefulness of big data in delivering proof of qualitative research areas.

Big data and datafication have penetrated many areas of people's daily lives to the point where many of the things that people do or see are somehow turned into data and measured. Big data also impacts the personal and social life of many people by changing the way that people communicate; nowadays communication is increasingly carried out via digital mediums rather than personal face-to-face communication. This also results in a higher demand for quantitative measures for backing up qualitative claims in all areas including social science research (Sweetmann, 2001). The rise of the data-driven economy and society that monetises data and the information we gain from it, is not only changing the way that people are communicating or how business is carried out (West, 2019), but it potentially has an impact on the way that research is performed. Because people are getting more used to metrics in every dimension of their lives and big data has become a heavily debated societal topic, we tend to expect more quantitative measures especially in the domains that have seen so far low use of such metrics (Everitt, Landau, Leese, & Stahl, 2011). Consequently, theoretical deductions are increasingly questioned in social sciences and the demand for more substantial and validated evidence based on quantitative methods is picking up (Sweetmann, 2001).

Social research and leadership research specifically are generally leaning towards the qualitative end of the scale, as it is focusing on the generation of theories and adopts a social view of reality that never reaches a stable state due to the element of human contribution (Bryman & Bell, 2015, p. 38). Quantitative methods are often disregarded in social sciences because they are believed to remove part of the subjectivity of the investigated phenomena and thereby simplifying too rigorously and classifying too coarsely. In short, quantitative systems remove too much of the metadata that explains behaviours and supports theory building (Bryman & Bell, 2015, pp. 629-635).

This clear cut between applying quantitative and qualitative methods has been a given so far in academic research; social sciences or sciences that put a high emphasis on words and their meaning preferred quantitative methods whereas natural sciences and everything related to mathematics favour quantitative methods. Traditionally neither of both areas is likely to pick the opposite set of methods even if it could be utilised. The emergence and establishment of big data, the abundance of generated data as well as the reduction of cost in mass data processing have the potential to revolutionise the ways that social scientists conduct their research. We argue that there exists an opportunity for employing quantitative methods even in social sciences where they generally have been less popular, because it allows for a different way of researching social sciences.

Applying quantitative methods to social sciences offers several advantages compared to only sticking to qualitative methodologies. For one, adopting quantitative methods forces scholars to change the way they make their points or arguments. Instead of relying on argumentative structures that should convince the reader, quantitative methods provide the reader with numbers that draw a clear picture and leave no room for argumentation because replicating the study with the same dataset and the same methods should deliver the same numbers as the output. Further, numbers and data can only be questioned in the way that they have been gathered, meaning that the data points themselves do not give in to stress tests; it is only the research design that could be subject to questioning the methods or the dataset delimitation. Lastly, with clear transcripts of the applied methods and dataset limitation, qualitative methods allow everyone to replicate the same study with same data and should, by the nature of quantitative research, arrive at the same results. There is no interpretation bias of the researcher or interviewer and interviewee bias included in quantitative research methods, because its core setup does not allow for these types of bias. The only stage in a quantitative study that is at risk for interpretation bias is the translation of the finding from the analysis into the discussion of these results and its implications. Despite this blind spot, it allows for only a limited amount of bias compared to qualitative methods.

1.1 Research question

Therefore, building on these advancements in big data techniques and attempting to blend quantitative methods with social research, we build this study around two research questions which are:

> ***Do clusters of words and word usage across academic, educational, and business contexts indicate the existence of leadership fashions, and the role of academics as leadership fashion setters.***
>
> ***To what extent can research techniques that collect and analyse Big Data enhance the study of leadership and management fashions.***

1.2 Structure of this thesis

In order to best answer our research question, we have chosen to separate the usual section of methodology found in an academic paper in to two separate chapters; Methodology I and Methodology II. Research philosophy and research design will be covered in Methodology I, followed by the chapter on literature review. Then the general data selection, description and handling will be presented in Methodology II. One reason behind this switch is an attempt to merge the 'templates' for qualitative and quantitative studies. The primary reason is the cohesiveness of the study and its progression, we believe that by first outlining the overall scientific understanding followed by a review of relevant literature and method choices before presenting the actual process of the data gathering, preparation and calculation, we create a better flow and easier understanding of the process and the end results. Based on this, this thesis will be structured as follows:

Chapter 1: Introduction

This chapter so far has briefly outlined the motivation, reasoning and relevance of this study and presented the research questions, that create the baseline for the rest of the study.

Chapter 2: Methodology I

Here we present our initial scientific frame. We determine our philosophy of science, setting the scientific understanding for the study. We conclude by presenting our research design thus, allowing us to create a frame of reference for further review of methods.

Chapter 3: Literature review

This is where we discuss the relevant literature, both in terms of articles and studies on the same topic, but also relevant methods for our analysis. We have separated this chapter in to two sections; articles related to topic and articles related to methods.

Chapter 4: Methodology II

This chapter provides a thorough presentation of our data selection. The chapter also goes into detail on the data gathering and processing of this study. This chapter is meant to create a preliminary understanding of the data for the reader before moving to the actual analysis.

Chapter 5: Analysis

In this chapter we dive into the backbone of this study. Here we present our quantitative analysis; we start broad in our approach and narrow down to more specific data before comparing our findings in leadership fashions with our findings in management fashions. We conclude this chapter by discussing our findings.

Chapter 6: Conclusion

Here we conclude on our findings and answer our research question, while reflecting on the method and data used and its limitations. We conclude this section by making recommendations for future research.

Chapter 2: Methodology I

In this chapter, we will go through our initial thoughts on the methodological handling of this study. By applying big data mining and analytical technologies to a study performed in the social science realm. We are introducing a quantitative element to an otherwise predominantly qualitative research area. This means that we need to establish our choice of research philosophy as well as our research design before moving on to investigate potential methods of conducting this study. Based on our knowledge that we wish to obtain and use big data and the inferred analytical tools that comes with it, we can create a basis for the rest of the study by determining the preliminary academic framework. By determining our philosophy of science and our research design first, we create a guide for our further research, both for the review of potential methods and theories but also in the execution of our analysis and the outcome of our findings. By establishing creating this initial frame, we establish a baseline of what conclusions can be produced by this study, hence, we create a guideline for ourselves in the further work with this study and its impact.

2.1 Philosophy of science

In this paragraph we will rationalize our choice of philosophy of science by comparing our choice with other philosophies that could be argued to be relevant for this study. The philosophy of science we have chosen is the epistemological and ontological view of critical realism. Since this is a study of the existence and factors of a potential phenomenon, the philosophy of critical realism will allow us to investigate this with the most appropriate understandings (Bryman, Social Research Methods, 2012). Based on the nature of this study, there are other philosophies of science that could help provide an epistemological and ontological framework for this specific problem, namely, positivism and social constructivism. In the following paragraphs, we will discuss the implications of all three philosophies.

Critical realism employs a realistic ontology, meaning that it is recognized that phenomena exist, and their processual essence can be analysed and investigated (Engholm, 2014). In comparison, a social constructivist philosophy would employ a constructivist ontology, which would not grant the phenomenon an essence and would therefore only allow an analysis or investigation of the emergence of the phenomena. A social constructivist view could be argued to be useful in this study, since it could be argued that trends and fashions are a product of social construction. Positivism allows for a realistic ontology but is more focused on potential predictions based on findings, since there is no need to argue for existence of a phenomenon once it has been found. Since we are aiming to investigate if a phenomenon occurs, how it diffuses and the factors involved in the phenomenon, we deem it more accurate to employ a critical realist ontology. Thus, allowing us to acknowledge the phenomenon for its essence while investigating its emergence.

In epistemology, critical realism aims to produce knowledge through abduction. Abduction in general terms means that inferring one phenomenon as the reason for another is a legitimate and validated reasoning, while knowledge produced through deduction builds on sound and consequential proof in what can be referred to as 'mathematical logic'. Inductive reasoning on the other hand allows for combination of arguments and proofs to constitute a consequence. Abduction will therefore allow us to make the simplest and most likely explanation of a given phenomenon or truth (Engholm, 2014). Again, in social constructivism we would see a more inductive approach to knowledge understanding. An inductive approach would mean that we would not be able to obtain the desired level of objectivity that would generate the validity needed to argue for the existence of a potential phenomenon. Positivism also holds a more inductive epistemological approach but is also often linked to the deductive approach depending on the topic of research, since there is the requirement of validity meaning that knowledge has to be proven or validated. This would in theory be applicable to this study, since we are conducting quantitative research. However, we are conducting quantitative research on qualitative data, it will therefore be difficult to obtain the level of objectiveness appropriate for a positivistic epistemology.

The concept of truth of the chosen philosophy is also important to our final findings and the validity of these. In social constructivism, the concept of truth relies on a systematic interpretation which cannot be contradicted, based on the inductive interpretation. In critical realism, the truth is based on the probability of its existence regardless of the interpretation by the researcher (Engholm, 2014). Positivism, like in the epistemology, relies heavily on objectivity and the validity of the findings, while critical realism allows for probability of existence positivism requires evidence of existence.

Based on the aforementioned elements of the mentioned philosophies, we believe that critical realism is the best ontological, epistemological and truth fit for this particular study. This philosophy will allow us to hypothesize the existence of a phenomenon while investigating the factors in the phenomenon itself and its diffusion. Critical realism will also allow us to accept a certain level of social constructivism in the occurrence of a phenomenon while analysing this using quantitative data based on qualitative data sources. Furthermore, critical realism allows us to present our findings as the truth we can present on the basis of this study, while accepting that it is not the absolute truth.

2.2 Research design

In this section, we will explain the nature of this study and the corresponding research design. This study takes three factors into account in the aim to enhance the understanding of leadership fashions as a phenomenon, this will be done with the help of RPA and web scraping of Business Schools (*Education*), Academic articles (*Academia*) and leadership development businesses (*Business*).

This qualifies as a quantitative study of qualitative data; in its design it is most similar to a discipline within bibliometric studies defined as the strategic approach (Kostoff, 1995). Bibliometric studies are in essence the numeric and statistical count, handling and presentation of items deemed informative for the given study subject. The strategic approach within bibliometric studies allows the researcher to evaluate the performance of a given discipline based on qualitative data (Kostoff, 1995). Bibliometric research is generally used in literature studies as a way of quantifying the process of written information. In most instances, bibliometric studies are conducted based on citations, number of articles in a given time frame and research area. All these factors are then mathematically and statistically calculated to determine the answer to the subject of the study. Based on this there is an element of this study that is similar to that of a bibliometric study. However, we are not investigating based on citations which is an important element in bibliometric research design.

We argue that this study holds elements of a bibliometric research design in the fact that the aim is to take a quantitative approach to qualitative data. This is very much the approach of a bibliometric study, even if the qualitative data obtained and investigated is not the same.

Another research design relevant for this study is the systematic review. Systematic reviews are another way of determining research impact, it is primarily used in the medical and health industry (O'Brien & Mc Guckin, 2017). A systematic review is a framework for selecting data to be analysed, it puts a high emphasis on eliminating as many biases as possible by focusing first on clear identification of data and then well-argued exclusion (Roberts & Petticrew, 2006). By first creating a thoroughly defined data mass and then focusing only on exclusion of clear breaches for the determined identification criteria, it aids in eliminating biases.

As aforementioned, the systematic review is primarily used as a tool in the health industry to compare research, journals and charts. What is interesting for this study is the framework used in systematic review. The framework allows for continuous review of data gathered, and the reliability and usability of said data. The framework also allows for several steps in data gathering and handling to take place (see Figure 1).

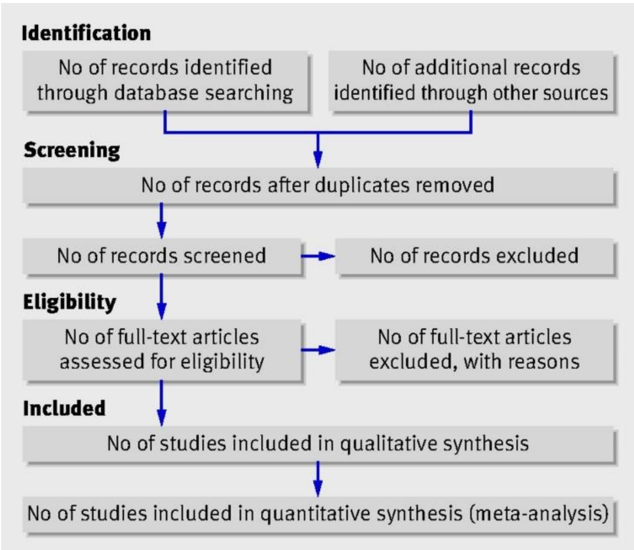

Figure 1: Data analysis process for a systematic review

We will use the framework from the systematic review to gather our data and for initial processing. We will use disciplines and elements of bibliometric research to further process the data into usable outcomes.

Chapter 3: Literature Review

The topic of our thesis is to investigate leadership and management fashions and the manner in which they diffuse using big data. We have found that we can question the notion that leadership and management scholars can be perceived as fashion setters.

The purpose of this literature review is to outline the theoretical and academic foundation of this paper by providing an introduction to and overview of the relevant fields of research. It will further show how different authors' contributions build on each other and where controversies between perspectives have arisen (Bryman & Bell, 2015, pp. 100-101, 117). Due to the novelty of the nature and scope of our research, using big data in a social science context, we have chosen to lean on the definition of a literature review posed by Hart in 1998.

"The selection of available documents (both published and unpublished) on the topic, which contain information, ideas, data and evidence written from a particular standpoint to fulfil certain aims or express certain views on the nature of the topic and how it is to be investigated, and the effective evaluation of these documents in relation to the research being proposed." (Hart, 1998)

Hart poses that there are two levels of a literature review, the why and the how. Firstly, reviewing literature that supports why the research topic is of interest and secondly reviewing literature which explains how the research is to be conducted. We have chosen to divide our literary review in to these two points, both because it appears logical but also to offer a sense of simplicity to a rather complicated research process. It will also help clarify our choices of topic and research methods.

We will start with reviewing articles that support our choice in topic of leadership and management fashions and their diffusion. As Abrahamson (1996) posed a framework for understanding management fashions first, we will start with an overview of management fashions that puts the foundational work of Abrahamson regarding management fashions into context. We will then go on to review the differentiation between management and leadership as Guthey has posed an expansion on Abrahamson's framework, arguing that this can be used for leadership fashions with his amendment, this will be our basis for continuing the literary review to leadership fashions. To conclude the section of why we are conducting this study, we will review the literature on diffusion of fashions.

In order to support and explain how we will conduct this research; we will review similar studies and literature arguing the approaches used in this type of research. These will stem from both social and natural sciences in order to provide a thorough overview of a rather new way of conducting research. We will conclude the section of how we will conduct our study, we will review literature and different definitions of big data to concretize what we define as big data.

3.1 Articles related to the topic of this study

3.1.1 Management fashions

Management fashions serve as the conceptual foundation for leadership fashions and are also relatively close in terms of their structure and workings. Additionally, the leadership fashions framework advanced by Guthey leans on Abrahamson's management fashions framework.

Abrahamson's framework for management fashions argues for the interdependence of supply and demand of management fashions that are further shaped by external factors like norms of progress and rationality as well as sociopsychological and technoeconomic forces (Abrahamson, 1996) (see also Figure 2).

Abrahamson (1996) was one of the first to formalise the concept of management fashions. He advances a duality of the content of management fashions, namely fashion setting as its process and management fashions as its outcome (Abrahamson, Management Fashion, 1996). This duality is although not enough for explaining why management fashions arise in the first place. Abrahamson argues that norms of managerial rationality and norms of managerial progress are driving managers' interest in novel managerial techniques. Both are societal expectations where in the first one managers are expected to use the most efficient management techniques to reach their goals and in the second one that managers employ state-of-the-art management techniques to keep up with development

(Abrahamson, Management Fashion, 1996). From here, Abrahamson develops a definition of a management fashion which he believes is "a relatively transitory collective belief, disseminated by management fashion setters, that a management technique leads rational management progress" (Abrahamson, Management Fashion, 1996, p. 257).

Jackson and Guthey tap into the time limitation element of management fashions, especially the consequences this has in the educational context. Both authors critique that management fashions are frequently disregarded in educational settings because of their "planned obsolescence" (Jackson & Guthey, 2006, p. 26) rendering them invalid in the view of many management scholars. They furthermore state that "management fashions come and go, but management education is supposed to be about timeless truths and first principles that can help prepare people for their careers" (Jackson & Guthey, 2006, p. 26); here both authors illustrate why the study of management fashions is incompatible with what traditional management classes teach to students. Students are supposed to obtain a management practices toolbox that is generally applicable but disregarding the fact that the best-suited practice might not be one that is universally applicable especially with the changing conditions of the business environment. Consequently, management fashions, despite their importance in providing a full picture of management practices, are pushed into the background when it comes to teaching in academic settings (Jackson & Guthey, 2006) because the contents of the fashion itself are prioritised over the overall dynamics behind fashions and what their implications for management fashion are.

When observing the management fashion setting process as outlined by Abrahamson, business schools are one of the actors contributing to the setting of management fashions. Now evaluating this model with the perspective of Jackson and Guthey, we need to ask ourselves how important the contribution of the educational sphere (business schools) to management fashions is, considering that their intent is primarily to teach management practices that are universally valid and applicable. In our analysis, we will also assess how large and important the contribution of business schools to leadership fashions is. Assuming that business schools' perspectives on leadership and management are not that dissimilar, our data and analysis of the latter can either support or reject the point advanced by Jackson and Guthey (2006).

In Abrahamson's General Model of Management Fashion Setting, firstly the co-dependence and influence of management fashion setters and management fashion users, each being the main drivers for either the supply or demand of management techniques and programs in a broader sense. The sociopsychological and technoeconomic forces, also depicted in the same model, represent the external factors to the management fashion setting process but still impact the demand of this process (Abrahamson, Management Fashion, 1996) (see also figure 2).

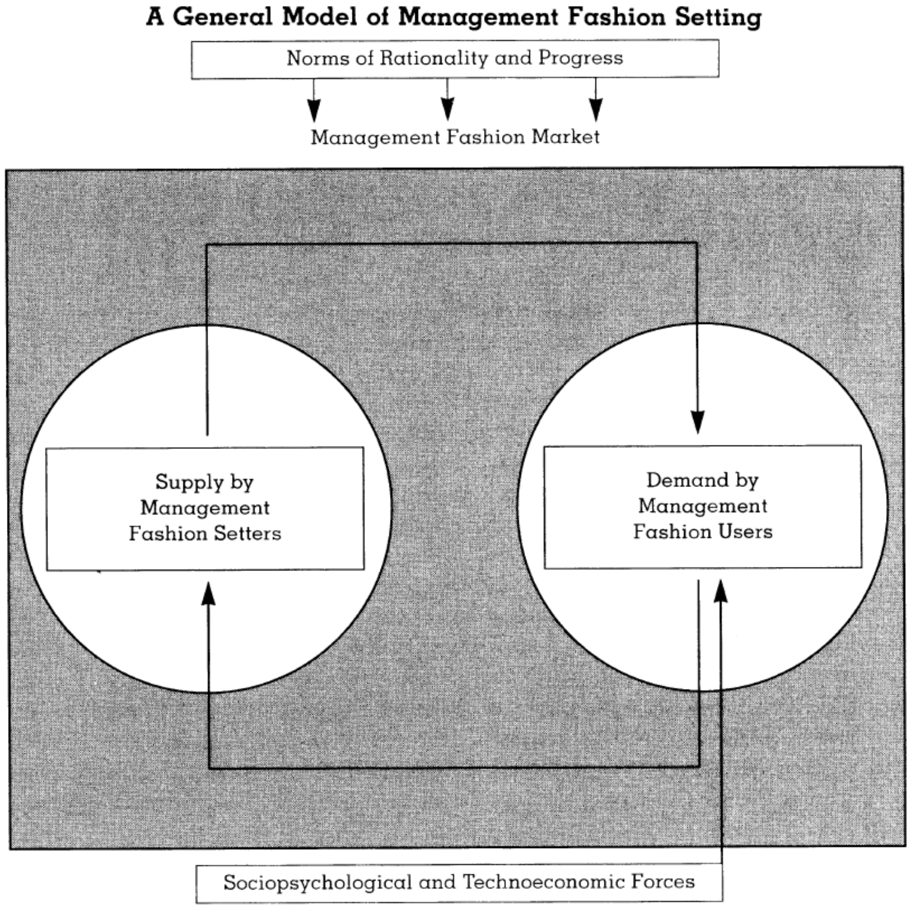

Figure 2: Abrahamson's General Model of Management Fashion Setting

Beyond explaining the general model of management fashion setting, Abrahamson further analyses the supply side of management fashion setters that run through four identified stages; these are creation, selection, processing and dissemination (Abrahamson, Management Fashion, 1996). Following Abrahamson's Management-Fashion-Setting

Process (see Figure 3 below), we understand that all the entities on the supply side including consultancies, business schools, gurus and mass media organisations are starting with their management fashion creation and selection phases once they detect a need in the demand sphere of management fashion users. Subsequently to these two phases, management fashion setters engage in the processing and dissemination phases of management fashion setting in order to launch new management fashions to the demand side which will eventually contribute to deciding on the dominant management design (Abrahamson, Management Fashion, 1996).

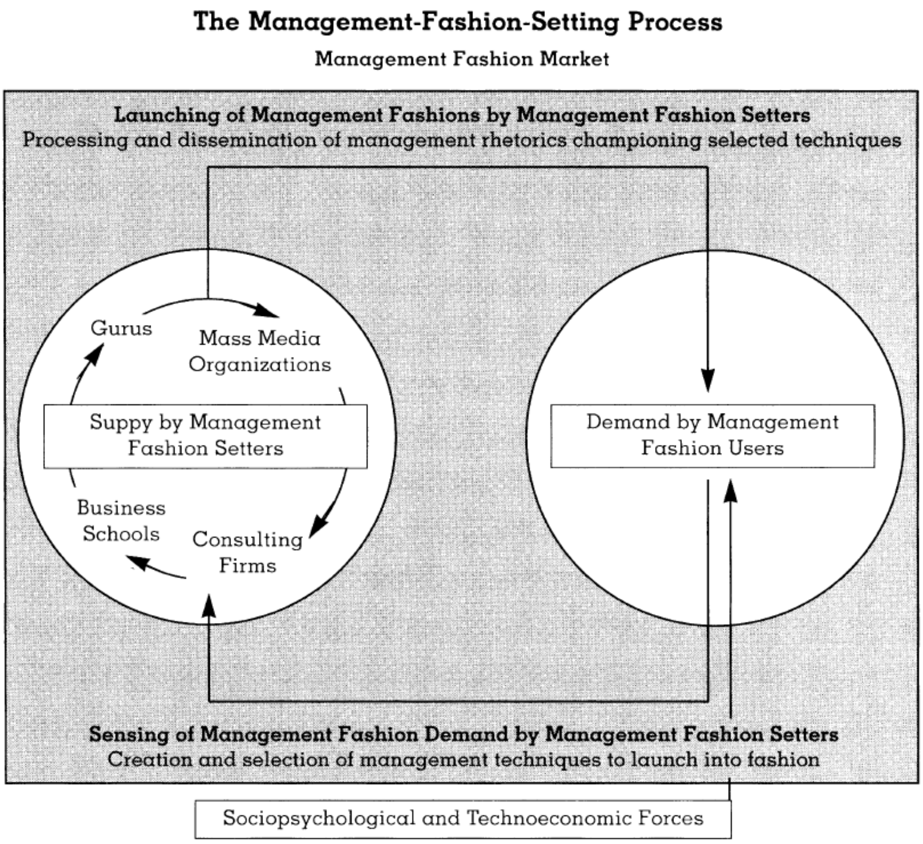

Figure 3: Abrahamson's framework for the Management-Fashion-Setting Process

There exists a multitude of different authors' contributions to the domain of management fashions to which Abrahamson (1996) has produced the foundational framework. An essential addition to the management fashion setting process outlined by Abrahamson (1996) is his addition together with Eisenman (2001) claiming that all the newer management fashions build previous management fashions thereby not building management developments on a blank slate (Abrahamson & Eisenman, 2001).

Newell et al. (2001) pick up on the emphasis that Abrahamson's puts on the essential role played by management consultants and gurus in the management fashion setting process. Abrahamson claims that the ideas developed and distributed by management scholars anchored in business schools become less important and perceived as less "valid" compared to other what other actors from the business context (consultancies, gurus, professional literature) develop. Newell et al. (2001) introduce the notion of "fashionisation of the topic of management fashion" (Newell, Robertson, & Swan, 2001, p. 5) to better understand how fashions get accepted and implemented by various actors. By "fashionisation of the topic of management fashions", Newell et al. (2001) understand the fact that the discussion of the arise and diffusion of management fashions becomes a fashion in itself. Abrahamson (1996) hints in his foundational research that the open gap created by scholars' underserved supply of new or advanced management techniques gets refilled with the techniques proposed by management consultants, gurus or mass media literature (Abrahamson, Management Fashion, 1996). This filled open gap then sparks the demand for ever newer and more advanced management methodologies, which in turn artificially creates and sustains the demand for management technique advancements. In other terms, Abrahamson (1996) outlines that business actors attempt to discredit the management technique work of scholars to create a favourable environment for the demand of their own products that triggers a steady demand for ever newer management techniques that gets supplied by the management consultants, gurus or the professional management literature (Abrahamson, Management Fashion, 1996). Newell et al. (2001) move away from Abrahamson's focus on the supply side and focus more on the dynamics between both the supply and the demand side of management fashions. They also raise the question what the contribution of the implementation side is to the entirety of the management fashion setting process. They see the demand side of management fashions as a critical element in the entire management fashion process because they have concrete ideas to what a newer management technique should add to and which issue the specific management technique should remedy (Newell, Robertson, & Swan, 2001). In this sense, it is a combination of what the demand side asks for and what the supply is able to provide hereby adding an element of social construction to the entire management fashion discussion (Newell, Robertson, & Swan, 2001).

Finally, Jackson and Guthey (2006) highlight that the whole discussion around management fashions uses a strongly technical vocabulary as well as proprietary vocabulary that attempts to legitimise management fashions as an important academic area of research (Jackson & Guthey, 2006). The entire management fashion topic has reached a complexity level that is far away from what management techniques were meant for; being useful methods to managers in mostly organisational contexts as a guidance to management-related issues. This resembles the situation that Abrahamson outlines: if the things that scholars provide get to technical and too distant from the hands-on problems that managers face, then the same managers will look elsewhere to find useful management methods that help them solve their issues and circumvent their obstacles (Abrahamson, Management Fashion, 1996) (Jackson & Guthey, 2006).

3.1.2 Leadership fashions

We will now review the literature in the domain of leadership fashions. This is the domain that we will also investigate with our analysis and provide insight into the existence of leadership fashions.

We see Abrahamson's framework as a good foundation for the framework of leadership fashions, because of the closeness of Abrahamson's framework for management fashions and Guthey's framework for leadership fashions. Both rest their frameworks on the dynamics of supply and demand of the respective fashions and distinguish themselves by different subjects of analysis and varying external factors influencing the respective frameworks. We further wish to emphasise that although management and leadership are often used interchangeably, they do not represent the exact same thing.

Guthey develops a similar model for leadership fashions based on the former model for management fashions. Guthey extends the norms impacting leadership production beyond the norms of rationality and progress that Abrahamson outlined for management production. Similar to Abrahamson, Guthey also bases their developed leadership fashion framework on the blended neo-institutional and production of culture perspectives (Guthey, Ferry, & Remke, work in progress). The difference that Guthey sees between management and leadership fashions is that the former are mostly concerned with providing efficient ways of reaching set goals whereas the latter is further considering a prioritisation of the goals based on moral, emotional and social expectations (Guthey, Ferry, & Remke, work in progress).

Hence, Guthey provides the following definition of leadership fashions given its existence:

> "Leadership fashions are relatively transitory, collective affirmations, co-produced by leadership fashion setters and consumers, that certain leadership concepts, discourses, or practices are both rational and progressive, because they provide new and improved ways to fulfil expectations generated by ever shifting configurations of norms of rationality, including practical, theoretical, formal, substantive and affective rationality." (Guthey, Ferry, & Remke, work in progress, p. 5)

With this definition, the similarities at the core of both frameworks become obvious; the similar elements are the time limitation, the collective belief as well as the rationality and progressiveness of a fashion/concept/practice. The differences start at the production of a fashion where Abrahamson advances that the management fashion setters are responsible for spreading novel fashions. Guthey on the other hand emphasises the combined efforts of fashion setters and consumers on pushing new fashions forward. He further stresses that rationality has multiple dimensions by drawing on Weber's (1964) categorisation of rationality and introduces the notion of "affective rationality" (Guthey, Ferry, & Remke, work in progress). The latter also represents an extension of the existing model of rationality by Weber and can according to Guthey be defined as the validation of social action via emotional legitimacy without recurring to formal norms, beliefs or values (Guthey, Ferry, & Remke, work in progress).

Figure 1.

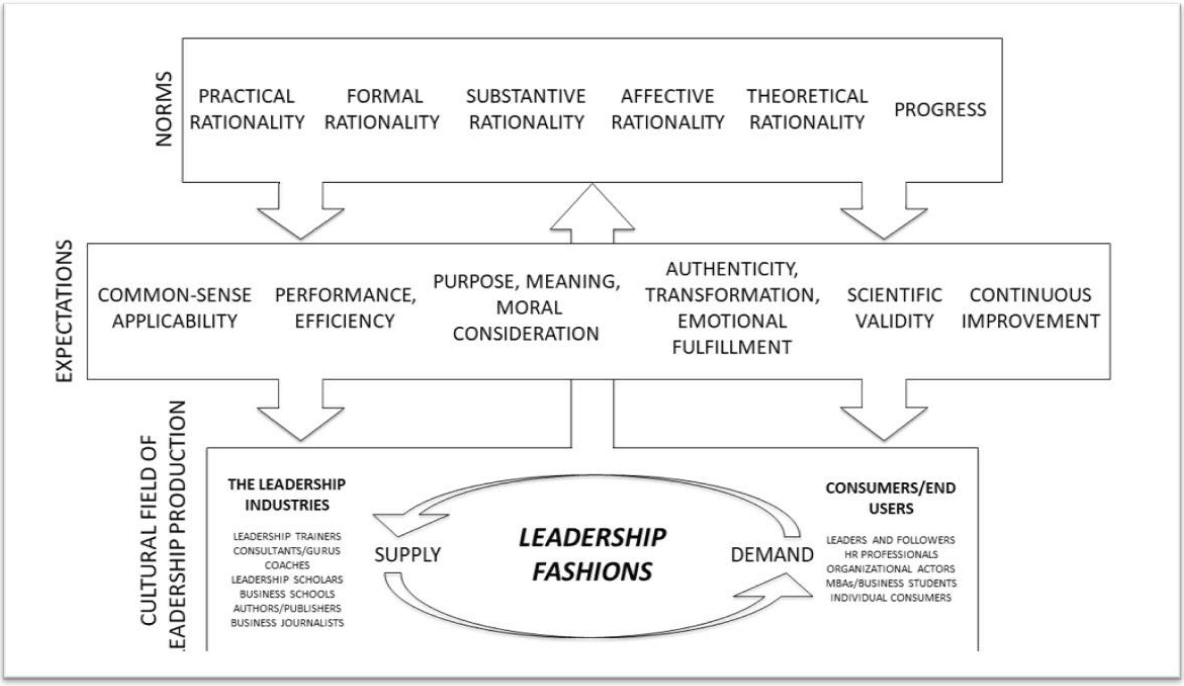

Figure 4: Guthey's framework of Leadership fashions

3.1.3 Diffusion of fashions

Sturdy defines diffusion as a version of the concept 'Translation' known from Latour (1986). Sturdy furthers the concept by stating that diffusion also covers the idea of innovation within an idea (Sturdy, 2004), meaning, for our study, that a fashion can see elements of innovation as it diffuses through the different areas of our research. We find this definition applicable for our study as we are investigating the diffusion of leadership fashions and management fashions and it only appears logical that a fashion would be subjected to innovation in the different areas of our research.

In order for a fashion to diffuse properly, it has to be legitimized, Perkmann and Spicer (2008) refers to this process as institutionalizing. They argue that for a fashion to be institutionalized it takes a large amount of institutional work across several actors of various skill sets (Spicer & Perkmann, 2008). They also argue that it can rarely be done successfully by one organisational entity. In terms of our specific study, it appears as though they are arguing against the idea of a potential fashion setter, which is aligned with what our findings show. It also aligns with the definition from Sturdy, if we accept the notion of innovation within a fashion as it diffuses, then it can be difficult to establish a fashion setter or first mover.

Scarbrough offers a further point of view to the idea of diffusion and innovation within. Scarbrough argues for the existence of intermediary groups of translators that serve to translate between different areas within the diffusion process (Scarbrough, 2002). Specifically, consultants are highlighted as intermediaries between the academic research area and the corporate business area. Scarbrough argues further that the intermediaries not only translate but adapts the current fashion to the need of their recipient. Thus, Scarbrough is supporting the notion as aforementioned from Sturdy of innovation within the diffusion process.

In our observation, it appears that there is a consensus among researchers of the topic of diffusion, that there is a level of innovation to be expected in the process. It aligns well with the idea of level of social constructivism in fashions as presented in earlier paragraphs. It also supports the point that it is difficult to determine a fashion setter. This is particular in the sense that if we accept the idea of innovation in the diffusion process within each area, then it becomes increasingly difficult to pin a starting point or root of a fashion. The fashion framework from Abrahamson presents the process as a circle allowing each actor to influence the other. This supports what we have found in the study of diffusions, by presenting the process in a circular motion we consent the fact that all actors are influenced by each other and a fashion is created, diffused and institutionalized, by cross organizational work across all areas. Yet it is fascinating that fashions are still researched as separate entities which we accept to be true, but yet to be factually proven.

3.2 Articles related to the methods of this study

As we have now accounted for the literature we believe supports our notion, that there is a lack of research to prove the existence of fashions and potential fashion setters in a factual manner, we will now discuss literature and studies that have inspired us on the manners in which we could conduct such a study. As we have chosen a to produce a rather large dataset for the purpose of this study, we will conclude this section by defining our data set as big data and go through a brief overview of the general understandings of said phenomenon.

3.2.1 Quantitative research

One of the most prominent ways in which leadership fashions and management fashions are researched today is through citation analysis (Clark, 2004). Clark critiques this method and claims that it does not provide a precise enough picture to be influential. The primary reasoning for this is based in the fact that citation analysis more often than not only handles academic research. Building on the earlier paragraph of this paper, we know that Abrahamson - among others, accept and points to the fact that there are several new actors appearing in the field of leadership fashions and management fashions research. These new actors, being consultants and gurus are most likely not accounted for in a standard citation analysis conducted through an academic research database. This is the issue that Clark is attempting to highlight. In our study we have found this to be accurate, while many researchers account for the existence of a fashion, they only account for the existence within the academic research area – which does not cover all the relevant actors who contribute and determine a specific fashion.

Another method was used in a study conducted by Scarbrough and Swan (2001) who uses an investigation of search terms in academic databases as part of the data collection. This particular study is investigating the diffusion and institutionalization of Knowledge Management as a management fashion (Scarbrough & Swan, 2001). This is also a common denominator in the research of leadership fashions and management fashions, to choose one theoretical perspective and research its origin, diffusion and institutionalization. Scarbrough and Swan chose to couple the data from search terms with a more in-depth analysis of academic articles on Knowledge Management and their contents. This approach does attempt to bridge the gap between qualitative and quantitative analysis, while it does provide an overview of the diffusion and evolvement of the concept of Knowledge Management, it fails to prove the existence of the concept as a management fashion as they do not compare the concept to other concepts existing at the same point in time, this is another point supported by Clark (2004).

Through our research of methods for our study we found that it can be stated that with the rise of quantitative analysis tools and access to much more quantitative data, the qualitative research approach is being critiqued. The expectation of factual proof and quantitative approaches to back up qualitative research conclusions is becoming more and more apparent. This is supported by Sweetmann (2001) who discusses the cultural debate and fashions theory. He stipulates that the cultural research area is experiencing criticism due to lack of quantitative backing of potential findings, that many critics find the methods to be text heavy and failing to account for the contextual setting of the researched topic or object (Sweetmann, 2001).

The limitations of the presented ways to conduct this type of research is further expanded on by Denrell & Kovács (2015). In this article, it is claimed that both the citation count and selection of specific theoretical themes to investigate introduces bias to a study. Bias in turn will diminish the legitimacy of any potential quantitative data the study may operate with (Denrell & Kovác, 2015). By introducing bias in a qualitative study, the researcher does not allow the quantitative data to speak for itself and can potentially prove false results by forcing the data into a certain form to fit a perspective, concept or theory. For most quantitative studies, researchers are taught to avoid bias at all costs, allowing the story to emerge from the data itself, as our preliminary review of literature has shown, these teachings do not appear to have extended to the area of qualitative research. This means that while quantitative research is enhancing and making an impact on the qualitative research area, the researchers are not well equipped to handle the data in a correct and non-biased manner (Everitt, Landau, Leese, & Stahl, 2011).

Another and more relevant approach to our study is the notion of scraping the internet. The idea of scraping or mining data is becoming increasingly popular amongst researchers, since it provides access to data that was previously unattainable (Everitt, Landau, Leese, & Stahl, 2011). It has become so popular in fact, that it has become a service provided by several online entities like Google (Marres & Weltevrede, 2013). Marres and Weltevrede (2013) argue that this is the start of a change in how research is conducted and the foundation on which social science researchers build their arguments and draw their conclusion. In short scraping or mining data means that researchers have the ability to obtain specific data from websites like all users of Instagram whom used a specific hashtag in the last week. As researchers we can either develop our own method of scraping or we can use one of the online services. For this study, we have opted to develop our own since we have the competencies, and the data we need is rather specific. This option will in turn provides with a very vast amount of data.

3.2.2 Definition of data

Big data is by no means a new term, because large amounts of data have already been circulating around the world since research has been carried out. The advent of the World Wide Web democratised the easy transmission and reception of information and data. This platform has also served as an enabler for big data accumulation and applications. We can also observe that different strains of research and industries are familiar to different degrees with the big data phenomenon (Hannay, 2014). Where the confrontation with big data is relatively common in natural sciences and research, it has become very popular in areas like social sciences and business.

To create context and meaning to big data, we emphasise different definitions of big data that we deem important to highlight.

Firstly, the Oxford dictionary defines big data as "extremely large data sets that may be analysed computationally to reveal patterns, trends, and associations, especially relating to human behaviour and interactions" (Oxford Dictionaries, 2019).

Another definition that builds on the definition by the Oxford dictionary is advanced by Mayer-Schonberger, namely that "big data refers to things one can do at a large scale that cannot be done at a smaller one, to extract new insights or create new forms of value, in ways that change markets, organizations, the relationship between citizens and governments, and more" (Mayer-Schönberger & Cukier, 2017, p. 6). Both definitions agree on the purpose of big data, namely that the output from big data should provide actionable insight or any other form of valuable information as the result of an analysis. They disagree although on the delimitation of the data input. Oxford Dictionary deems an extremely large size of the data set a sufficient criterion to categorise the latter as big data, whereas Mayer-Schönberger and Cukier see the necessity of large-scale analytics as the defining criterion for big data. We propose a combination of both perspectives by combining the extremely large size of the data size on the one hand as well as big data analytics as the only possible way to distil meaningful information from the data set on the other hand as the defining criteria for big data.

A third perspective on how to define big data has been advanced by George et al. with focussing on the size of the individual information “snippets”/elements contributing to a data sample. They argue: “For us, the defining parameter of Big Data is the fine-grained nature of the data itself, therefore shifting the focus away from the number of participants to the granular information about the individual” (George, Haas, & Pentland, 2014, p. 2). They pursue a different track by emphasising the minimalism of the information units/elements. We identify a link to Mayer-Schönberger and Cukier and their large-scale criterion, because a single grain of information would be useless without the necessary scale to identify relevant patterns and deduct information from these. It is similar to many different atoms constituting a molecule; without the specific composition that makes a molecule, the single atoms are only of limited use. It should nevertheless be noted that the granular information contained in big data sets does not necessarily need to be information about an individual but can originate from a varied number of different sources.

Further, data or big data itself without any context or further analysis is relatively useless because by simply looking at huge amounts of data, no meaningful conclusion can be made from this data. The data needs to be augmented in some way in order to understand its contents and deduct any relevant action from it. Examples for prominent methods connected to big data are machine learning and web analytics (George, Haas, & Pentland, 2014).

George et al. (2014) argue that “Big Data is fast becoming a tool that not only analyses patterns but can also provide the predictive likelihood of an event” (p.1). We argue that big data itself is not becoming the tool for all these applications, but that it is just an enabler. It is the analytical concepts and methods attached to big data that are the tools that analyse patterns and can provide predictive assessments and recommendations.

To summarize, we argue that big data enables due to its size, the relevance of its input and via the adequate use of quantitative, analytical methods a meaningful recognition of recurring patterns and hereby derive actionable insight and/or valuable information.

3.2.3 Cluster analysis

Based on the aforementioned findings, we as researchers chose to move beyond the scope of our education to find other methodological solutions that would fit our research purpose better. Looking into methods from natural science, we found an article by Elselvier (2015). Elselvier discusses the research of a population, and the methods that are available within that research scope (Elselvier, 2015). One of the more common ways to conduct population research is using cluster analysis – especially when dealing with large amounts of data. A cluster analysis is a statistical tool that allows the researcher to investigate how the different data observations act in relation to each other. In other words, a cluster analysis is a tool to asses if a large amount of observations can be summarized together in a meaningful way in smaller groups which resemble each other and which are different form other observations in a noticeable capacity (Everitt, Landau, Leese, & Stahl, 2011).

In light of our findings in this literature review, we believe that a cluster analysis is the most likely to provide the least bias while maintaining the integrity of the datasets. By grouping all words together in clusters, it will provide us with a clear image of reality, rather than one we constructed ourselves based on assumptions we made. In order to understand the significance of this, it is important to understand the amount of data we have. We have previously stated that the research foundation of this paper is big data, in the following section we will present different definitions of big data, in order to shed light on a rather complex and undefined phenomenon.

3.3 Key Takeaways

The reason why we decided using the three factors *Academia*, *Business* and *Education* traces back to the perspectives of actors outlined by Abrahamson and Scarbrough. The view of each of their arguments led us to choose our aforementioned three factors. To recapitulate their views, we will briefly mention them once again.

In Abrahamson's framework, a list of actors within the supply side of management fashions is advanced. Abrahamson argues that the combined efforts of consulting firms, business schools, gurus and mass media organisations constitute the supply side of management fashions (Abrahamson, Management Fashion, 1996). Furthermore, Scarbrough supports this point and Clark (2004) argues that this surge in actors is one of the reasons that the research has gone too far, and become repetitive (Clark, 2004)

As this shows, the three factors *Academia*, *Business* and *Education* we chose is then a synthesis of these authors contributions. Our *Academia* branch combines the (conceptual and) research perspective of Clark with the mass media organisations actor of Abrahamson – with the assumption that publishers of scholarly, peer-reviewed articles also figure under mass media organisations. The *Business* branch then synthesises Scarbrough's practice perspective with Abrahamson's actors called consulting firms and gurus. Finally, the *Education* branch aggregates again Scarbrough's practice perspective with the business schools that figure in Abrahamson's framework.

By cementing the theoretical background for our choice of research topic. We have determined that the best way forward is to conduct a cluster analysis, which will both allow us to eliminate as many biases as possible, allow the data to tell the story and analysing big data as it is supposed to be investigated. This will also allow us to look across our three areas of research with the same method and vigour. Secondly, it will eliminate our preunderstanding as researchers, since we will have no control of how the data is selected.

Chapter 4: Methodology II

In order to best answer our research question, we established that a cluster analysis would be the appropriate measure. A cluster analysis will allow us to estimate if fashions exist, where they originate from and how they diffuse. In this chapter, we will explain the necessary steps that has to be taken I regards to the gathering, preparing and processing this data before a cluster analysis can be conducted.

Due to the large amount of data processed in this study, it is necessary to delimit the number of entities in each of our three samples. We further give them specific and easily distinguishable names to facilitate the reading of this paper. In the following, the term *Academia* represents the database of articles from our sample that are intended to reflect academic developments in the field of leadership. Secondly, the term *Business* refers to all the leadership development, executive search and consultancy firms that constitute our sample. And lastly, *Education* encompasses all the triple-accredited business schools that are part of our sample.

4.1 Dataset Description

Our study will be based on two separate datasets, one is the gathered data for leadership fashions and the other is for management fashions. Each of the two datasets contains three subsets; Academia, Business and Education, the datasets span over ten years from 1st January 2008 till December 31st 2018. In total for the two subsets, we have accumulated a data mass of approximately 166.807.182 individual data points in raw data before processing and handling. After collapsing the data to our specific purpose, we end up with two datasets that contain a total of 57.508 values that corresponds to the cumulated frequency of a specific word in a given year.

As aforementioned, this amount of data and the relevant data processing belong in the category of big data. Therefore, we will now account for how the data was processed and prepared for the analytical purpose of this study. We will start by accounting for the data collection itself, meaning where the data came from. Secondly, we will account for the way in which the data was gathered, the tools and skills used. Then we will go through the processing of the data and how it was prepared for further analysis. Following the processing of data, we will go on to the handling of said data explaining how we wish to work with the data and analyse the results. Finally, we will conclude this paragraph by reviewing the limitations of our datasets and potential alternative analytical approaches to the gathered data.

4.2 Data Selection

Selection of *Academia* (academic literature)

The limitation in *Academia* is primarily due to the technical restraint regarding the databases where the articles are available. Based on meetings with the librarian at Copenhagen Business School and our own knowledge and abilities, we chose to use one online database for the *Academia* data. We chose the database 'Business Source Complete' (EBSCO Industries, Inc., 2019). Business Source Complete allowed us the most accurate selection criteria and also returned the most hits compared to other databases. The database was set to look for peer-reviewed and scholarly articles in the time period of January 2008 until December 2018; furthermore, the subject term was set to 'leadership' or 'management' with the inclusion of the word 'people' in the case of 'management'. This gave us a database of respectively 16.612 and 11.202 articles between 2008 and 2018. We decided to gather data on the articles from abstracts alone rather than the full article.

Selection of *Education* (Business schools)

For the selection of *Education*, only universities or business schools were chosen that hold a so-called triple-accreditation. This triple-accreditation consists of three different accreditations by three independent accreditation agencies across the world; these are AACSB (Association to Advance Collegiate Schools of Business), AMBA (Association of MBAs) and EQUIS (EFMD Quality Improvement System). The list of accredited schools varies from accreditation to accreditation and these are not the only university accreditations available on the market. These three accrediting agencies are although those whose combined accreditation provides a university with the discussed triple-accreditation. An online list of schools showed that only a total of 130 universities worldwide have the three combined accreditations (Find MBA, 2018). We transferred the schools contained in this online list to an Excel file prepared for further analysis. In order to also analyse the development of the scope of the university, a time-sensitive delimitation was necessary. The selected criterion required that each webpage existed in 2008 allowing for an analysis of their webpage over a ten-year period. To verify that the current domain of a university already existed in 2008, we used the online tool "Internet Archive: Wayback Machine" to see for which past dates records of the respective websites were saved. The Wayback Machine is a repository of historic websites and saves older versions of the same website thereby allowing us to view and search older, timestamped versions of a website (Internet Archive, 2018) (see Figure 5 below). All the schools whose website did not exist under the same domain in 2008 were removed from the sample, resulting in a final list of 48 universities worldwide. Besides the name of the university, also their country, the date of the first registration of the university's domain and their URL was saved in the aforementioned Excel table. This metadata allows to further finetune the conducted analysis by allowing to see if any potential trends are not only time-sensitive, but also subject to geographical trends.

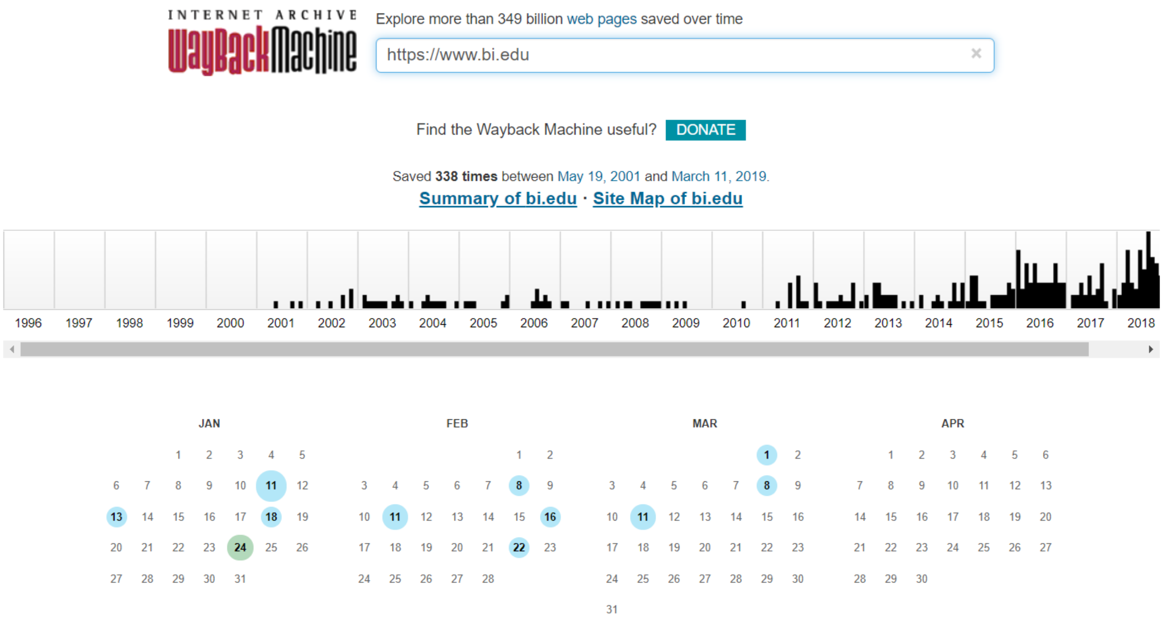

Figure 5: Screenshot of Wayback Machine

The hereby created sample of 48 schools is composed of schools from all continents and thereby allows us to derive patterns in leadership and management developed at business schools on a global scale and not only on a regional scale. Further, by choosing schools that carry the triple-accreditation also provides a list of schools that fulfil some minimum standard of teaching and research quality which made it unnecessary for us to develop proprietary criteria for choosing higher education entities.

Selection of *Business* (companies)

Similar as for the schools, due to size and scope constraints of our work, only a limited amount of the commercial industry could be sampled making it necessary to develop some sort of selection criteria for organisations offering leadership development products and services. After rejecting several lists compiled by different entities because of the subjectivity of their selection criteria, we found the Association of Executive Search and Leadership Consultants (AESC). We decided in favour of this association's membership list over other membership or accreditation lists because of their clear and comprehensive membership criteria. Following our judgement, the membership criteria as outlined by AESC ensure a level of quality for the compiled leadership development companies and therefore makes their list a relevant overview of the leadership development industry which will be also used for this thesis. A total of 239 companies are members of AESC as of March 2019 (Association of Executive Search and Leadership Consultants, 2019). Similarly, to the list of universities, we established a list of these 239 leadership consulting and executive search companies in Excel. Again, other meta-data including the location of their headquarters or their operating market, the first time the company's webpages was registered at the above-mentioned "Internet Archive: Wayback Machine" tool and their URL. To ensure that the observed periods for the universities and the companies coincide, the sample condition as for the universities was required, namely that a company's website already existed in 2008 under the same domain. When sorting out the companies whose website under the specified domain has not existed in 2008, we received a list of the remaining 129 companies of originally 239 AESC membership companies that are the basis for this analysis.

4.3 Data Collection: Methods and Tools

The collection of data accounted for in the earlier section was conducted using the techniques of Robotic Process Automation. Robotic Process Automation or RPA refers to a "software robot" that can be set to do automated tasks like gathering data from websites into databases for further investigation – which is the case for our study. RPA is in its simplicity a piece of code that generates specific commands to be executed by the computer in a specified succession. We used two separate tools to develop the RPAs for this study, Unified Functional Testing – a tool specifically for RPA development supplied by HP, and the underlying coding module in Excel; Visual Basic for Applications.

For the purpose of this specific study, we concluded that three RPAs were necessary. One was coded for the purpose of scraping the abstracts of academic articles from the database Business Source Complete. The second RPA was coded to gather all the underlying URLs of the chosen Business and Education websites. The third RPA, building on the data gathered by the second RPA, was coded to scrape each website for text containing either the word 'leader' or 'management' dependent on the dataset.

The RPA for the academic database was run twice to account for the two separate datasets, as aforementioned. It was run once with the subject term 'leadership' as a criteria, for all peer reviewed articles from 2008 till 2018 and a second time with the subject term 'management' and an inclusion of the word 'people' in the abstract as criteria, again for all peer reviewed articles from 2008 till 2018. Thus, creating the offset for our academic subsets within leadership and management.

The second RPA constructed to obtain URLs or 'sub websites' of the chosen list of company (Business) and business schools (Education) websites was only run once, as the list of URLs would not change between each of the two datasets. The obtained URLs were then separated out based on the subset they belonged in. Thus, creating two separate lists of URLs, one for Business and one for Education each containing a full list of all URLs to scrape for text.

The third RPA, for scraping text from websites was run a total of four times. The four runs were categorized by dataset and subset, where the dataset determined the word the RPA searched for and subset determined the list of URLs the RPA searched in this provided four separate subsets; 1. 'Leader' in Business 2. 'Leader' in Education 3. 'Management' in Business and 4. 'Management' in Education. This left us with a total of six separate subsets, these are summarized in the following table:

Dataset	Subset
Leadership	Academia
	Business
	Education
Management	Academia
	Business
	Education

Figure 6 Overview of initial datasets and subsets

For the current state of each subset, they are merely a list of observations. Each observation contains the publishing year for Academia or year of URL caption for Business and education, the author for Academia or the specific URL for Business and Education and the captured text either as an abstract for Academia or a text string for Business and Education.

4.4 Data Pre-Processing: Methods, Tools and Techniques

Firstly, as aforementioned in the presentation of the systematic review, we remove duplicates in all six datasets. This procedure is the primary reason that the URL and author are stated in the database, these two datapoints allow us to be sure that a duplicate observation is truly a duplicate and would cause skewness in our analysis of the data. This left us with the following number of observations based on datasets and subsets.

Dataset	Subset	Observations
Leadership	Academia	16612
	Business	15678
	Education	8592
Management	Academia	11202
	Business	3941
	Education	7788

Figure 7 Overview of datasets, subsets and observations

In order to conduct a cluster analysis based on word usage across all subsets within each dataset, we need to establish number of unique words in each dataset. For this purpose, a fourth RPA was developed in Visual Basics for Applications this RPA looked at all text strings and abstracts of all three subsets of a dataset and determined each individual word along with the amount of times the word was used. The dataset for Leadership contained 37.968 unique words within a total of 40.882 unique observations, while the dataset for management contained 42.734 unique words in a total of 22.931 unique observations. We determined that for the purpose of our study it would be logical that a word had to be used a minimum of 100 times in order to be relevant in terms of estimating a fashion. Only taking words used a minimum of 100 times provided us with 2614 unique words for the leadership dataset and 2419 words for the management dataset. For the purpose of this RPA it was commanded to ignore several words deemed irrelevant for this study.

Once we had established the unique words we wanted to use, we transformed each dataset to document which unique words were used in which observation. This was done by using the VLOOKUP function in Excel, searching for each unique word in each piece of text or abstract observed. After this, we imported each subset into the statistical program R, here we deleted the column of text observations and URLs or authors, then we collapsed each subset by year. Thus, providing us with six subsets that state the frequency count of each individual word per year.

The frequency count was then normalized and transformed to a percentage of all words used in that given year. This was done to create a more accurate picture of the word frequency of a unique word in comparison to all words used that year. We deemed this number as the aggregated explanation rate, these values will provide the base for the rest of our analysis.

Chapter 5: Analysis and findings

Throughout the analysis we will find answers to our research question where with the usage of words and clusters of words across academic, business and educational context we will shed light on the existence of the leadership fashions and the role of academics as leadership fashion setters. Thanks to our employed big data techniques, our study provides richer insight into the workings of leadership and management fashions as well as their diffusion. It further calls into question the role attached to academics as fashion setters and the ways that researchers have analysed them previously. Our big data analysis of clusters of words and clusters neither indicates the diffusion of leadership fashion across Academia, Business and Education nor confirms the presumed role of academic scholars as leadership fashion setters. Towards the end of our analysis we will also provide a short comparative analysis with management fashions as leadership and management fashions are strongly intertwined and essentially derivative despite marginally different focus areas. We come here to the same realisation that our big data analysis can neither confirm the academics' role of fashion setters nor that management fashions do not exist.

Due to the vast dataset accumulated throughout this research, we could not find an adequate statistical approach within social sciences to draw any meaningful conclusions to our research question. Drawing inspiration from natural sciences, we have opted for a method that is usually used to map genetic markers within species. This method, better known as a cluster analysis, allows us to look at the usage of words across all three subsets (Academia, Business and Education) in a comparative manner.

The cluster analysis allows us to determine words within our dataset that behave in a similar manner over time; meaning that a cluster is a group of words that correlates to each other more so than other words thus creating a cluster.

The first step required for a cluster analysis is to create NMDS plots. These plots show the overall correlation between chosen elements of the dataset. We created a first NMDS plot that placed all three subsets onto the same map to visualize potential similarities or differences between the subsets. This showed us that there were next to no similarities between the three subsets, as they were all grouped separately with no overlaps. Then we plotted each subset (Academia, Business and Education) in a separate NMDS plot containing only that specific subset. This showed a logical progression within Academia and a more disperse distribution within both the Business and Education subsets.

Concluding that the three subsets and the underlying clusters behave in vastly different ways, we created heatmaps for each subset. Heatmaps generate a visual representation of the correlation (of the words) within a dataset. This allowed us to determine the clusters within each dataset. By extracting the clusters and the words a cluster contains from the heatmaps, we were able to create graphs showing the development of each cluster over the observed timeframe.

Our cluster analysis is based on the aggregated mentions of each word, meaning that each word is prescribed a value corresponding to its importance in percentage compared to all words analysed. By creating an aggregated dataset, we can look at each cluster in a comparative way over time, hereby allowing us to pick out certain words we would assume to be determining of leadership fashions (transformational, authentic and complex) and following the development of that surrounding cluster.

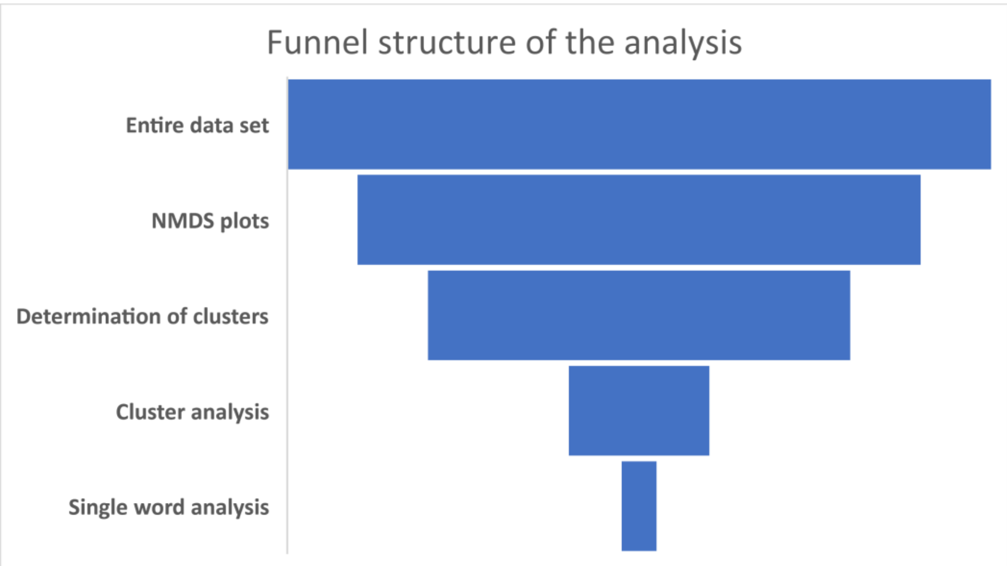

Figure 8: Structural overview of the forthcoming analysis

5.1 NMDS Plots

To gain an insight into the diffusion of leadership fashions, we analyse so-called NMDS plots that allow us to see how the three subsets are related to each other, thereby facilitating our understanding of the modes of diffusion. The NMDS plots that we created and show below are the first indicators that question the role of academics as leadership fashions. Despite seeing leadership fashions in Academia, we have no conclusive proof of their diffusion across Academia, Business and Leadership.

The NMDS (non-metric multidimensional scaling) plots are used to place the gathered data into a two-dimensional map showing how similar or diverse the different parts of the data are. One data point on the graph represents one year (out of the observed time period between 2008 and 2018) for one of the three subsets (Academia, Business & Education).

The input for the NMDS plot is the frequency count for each word and each year normalised and transformed into percentages to remove any potential bias created by solely using the absolute numbers for how often a word has been mentioned. Normalising the values into percentages makes the word counts comparable across the different subsets that we have analysed. The x- and y-axis depicted in a NMDS plot are non-metric meaning that no numeric statements based on the position of the data points can be made. Its purpose is to show the relative proximity or distance of a data point or a group of data points to each other. This therefore only allows to make comparative statements between different data points, e.g. data point A is closer to data point B than is data point C to data point B. This comparative nature of the statements that can be made from NMDS plots is also a limitation of NMDS plots. Further steps of analysis are required to gain deeper insights into the behaviour of single or groups of data points.

5.1.1 NMDS – all data (all 3 subsets)

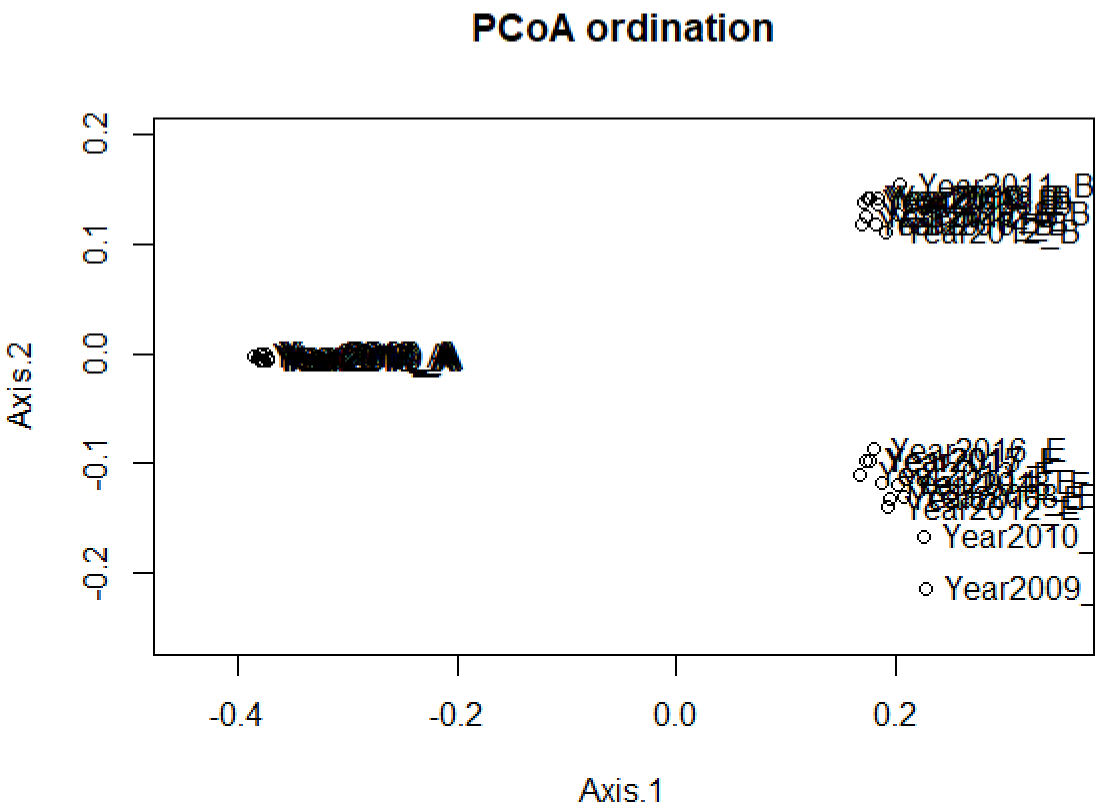

Figure 9: NMDS plot for all Leadership subsets

The above-shown graph places 33 data points into a NMDS plot. The 33 data points are composed of a data point for each year per subset (11 years analysed for 3 different subsets; A for Academia, B for Business and E for Education). The graph shows that the three subsets for Academia, Business and Education are very distinct from each other, meaning that the language used within each subset is more similar to itself than to any of the other two subsets. Each subset is depicted with strongly overlapping groups of data points for each subset. Academia shows the strongest overlap, meaning that the language used within the Academia subset is relying on a narrower and more strongly delimited vocabulary compared to Business and Education. In this particular instance, the subset Education shows the biggest variation in vocabulary in relative terms compared to Academia and Business which is shown by the weakest degree of overlap for its data points.

We can further see that the distance between Academia and Business as well as between Academia and Education is very similar and only minor differences in distance can be observed. This means that the language used within each respective subset is different between Academia, Business and Education. Following the placement of the Business and Education data groups on the aggregate NMDS plot, we find that the language used in Business and Education are more or less dissimilar from Academia by the same extent/margin without being the same within Business or Education. Business and Education are located very closely to each other on the x-axis (axis 1) ordination but are considerably apart on the y-axis (axis 2) ordination.

By interpreting this graphical representation, we can assume that the language used in each subset differs from the language used in another. We are unable to derive any more insightful meaning from the above-shown NMDS plot at this stage of the analysis; other analytical methods are better suited in providing richer insights into word patterns and usage patterns within each subset as well as over time. Before diving into a further refinement of our findings, we will also draw NMDS plots for each of the subsets in order to show the composition of each subset after that we have provided a rough placement of the three subsets combined in a single graphical representation.

5.1.2 NMDS – Academia subset

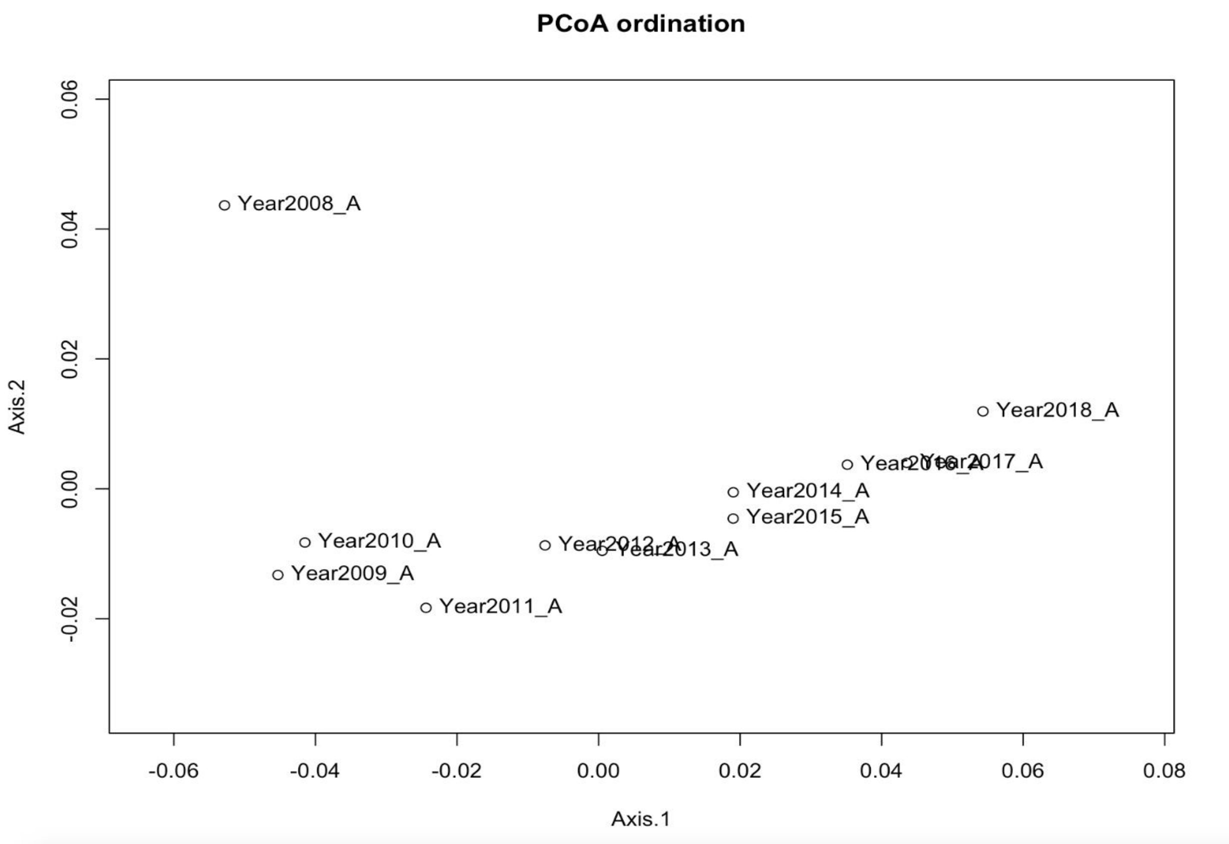

Figure 10: NMDS plot for Academia subset

This NMDS plot only shows the data points for each year in the Academia subset. The data points of the Academia subset develop over the years in a curve-like fashion indicating that the development of the words over the years is relatively constant and of an incremental nature. Only the year 2008 seems to be an outlier out of an otherwise almost linear relationship. For the rest of the observed years (the years 2009 to 2018), we can assume that the words used do not change dramatically from year to year, but that they develop in a more evolutionary fashion. A reason for their evolutionary way of developing over the years can be the created language standards in academic research, especially for articles that will be published in periodicals and journals. Academic journals usually have stringent criteria in terms of content, language and structure for authors that wish to publish their articles (Murray, 2013). Another reason can be the normativity of language used in the academic context in order to gain recognition as an academic fellow and foster credibility for one's research. The fact that much of the novel research conducted in academia either builds on prior constructs by other scholars or attempts at contradicting existing findings and theories, can also be a reason for the similarity and the linear development of the vocabulary used in our Academia subset.

From the graphical representation of the Academia subset, we can easily identify four clusters composed of two years each (e.g. 2009 & 2010; 2012 & 2013; 2014 & 2015; 2016 & 2017) signifying that potential changes in lead words used would happen in Academia when jumping from one two-year cluster to the next one. This curve-like and chronologic development is a further indication that words and composition build on each other instead of radically changing from year to year, hereby creating considerable stability in the vocabulary used in Academia to describe leadership. This also confirms what we have seen on the first aggregate NMDS containing all three subsets, namely that Academia uses the most uniform vocabulary to describe leadership as shown by the highly overlapping data points for Academia. We expect less consistent developments over the observed years for the two other subsets which we will analyse below.

5.1.3 NMDS – Business subset

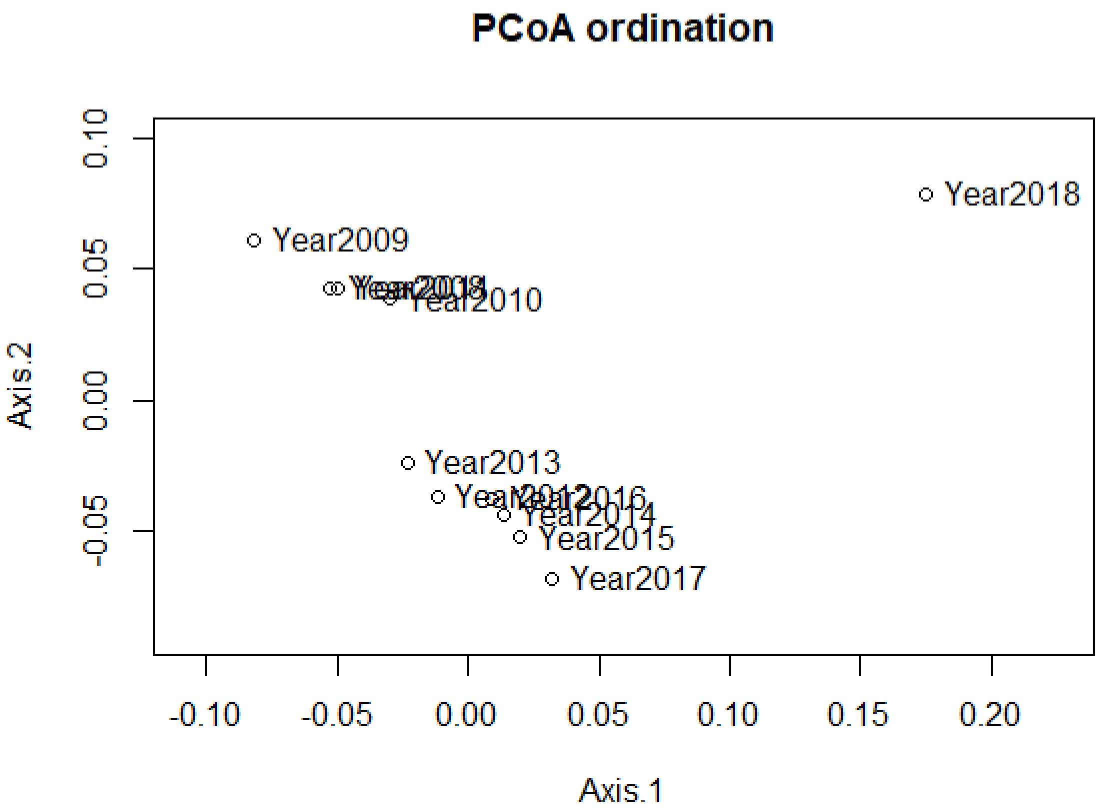

Figure 11: NMDS plot for Business subset

The NMDS plot for the Business subset offers a different picture compared to the Academia plot. Here we are missing the linearity of the chronologic and incremental development and see three larger clusters; one cluster containing the years 2008 to 2011, the second cluster containing the years 2012 to 2017 and lastly as the third cluster contains only the year 2018. This clearer separation between each cluster and also the stronger overlaps within each cluster, are the first indicators that the same words are used for longer periods of time, but then change abruptly rather than in the evolutionary fashion that we have seen before for the Academia subset. It also becomes apparent that the year 2018 is completely segregated from the rest of the analysed time period by being positioned in the upper right corner of the NMDS plot.

Based on the Business NMDS plot, we can already state that changes in vocabulary happen more frequently if more subtly and coherently in Academia, whereas Business sticks for a longer amount of time to the same vocabulary; as shown by the higher number of years that belong to the same cluster. Nevertheless, the NMDS plot for the Business subset still keeps a somewhat chronological order in its development, meaning that the developments happen on an ongoing basis over the years and do not jump back and forth along the course of time.

Further analysis is nevertheless required to identify the origin for this pattern and verify if the words change this drastically from one cluster to the next; in other terms if the vocabulary remains relatively stable over a couple of years and then changes noticeably.

5.1.4. NMDS – Education subset

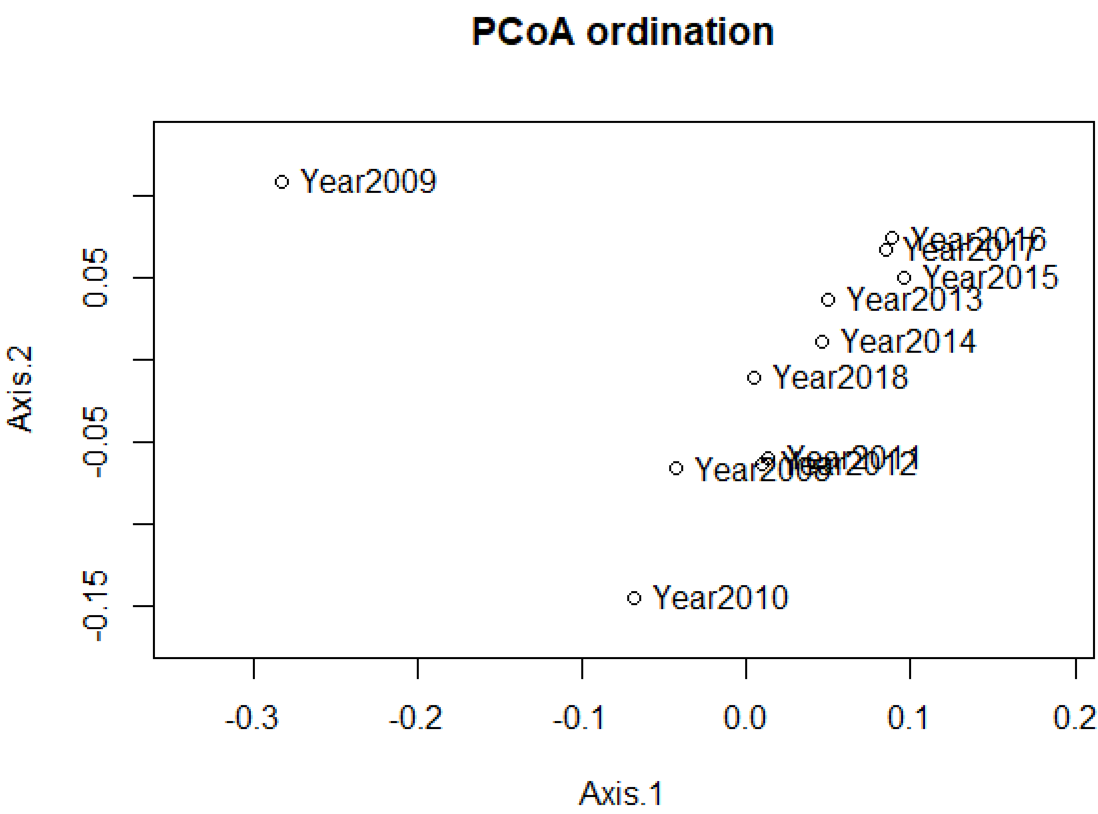

Figure 12: NMDS plot for Education subset

Finally, the NMDS plot for Education offers the least clear-cut image of the three subsets that we have analysed. It does not follow the clear chronological development over the years that we could observe for the Academia or Business subsets. Nevertheless, we can also for Education delimit four clusters: the first one being only the year 2009, the second cluster only containing the year 2010, the third cluster encompassing the years 2008, 2011 and 2012 and the last cluster containing the years 2013 to 2018.

One thing that is interesting to see, is the position of the 2009 data point which is completely offset from the other data points. Even though that the year 2010 also is offset from the rest of the data points by quite a margin and hereby creates a cluster on itself, we can still imagine a somehow linear relationship between all the years besides the year 2009. Further down in the analysis, we will be able to see that the word frequency counts for the words in 2009 are considerably different to all the other years for the Education sample, which can be the explanation for the position of the 2009 data point in the Education NMDS plot.

If we look back to the aggregate NDMS plot that included all three subsets, we could also observe that these data points had the lowest degree of overlap which is also reflected on this Education-only NMDS plot. Additionally, we can easily differentiate the Education data points for the years 2009 and 2010 on the aggregate NMDS plot from the rest of the overlapping data points which we also see reflected in the NMDS plot that only represents the Education data points. We can expect to see the same strong variations for the years 2009 and 2010 in the Education subset in the forthcoming steps of our analysis, but that the more refined analytical methods facilitate our understanding of the origin of these outliers.

5.2 Determining Clusters

After having plotted each of the subsets in the above-shown NMDS plots, we are interested in seeing which words are correlating and thereby creating clusters. When words correlate with each other, this means that they have either a positive or a negative relationship with each other. When words have a positive correlation, this means that the words increase or decrease in the same direction, whereas when words have a negative correlation, it means that words grow or shrink in opposite directions respectively (Wheelan, 2013). Where the NMDS plots helped us gain an initial overview of the closeness of the word composition for each year and subset, the cluster and correlation analysis allow us to break this down to groups of words. The clusters are critical in helping us to answer the question of how words and clusters of words exist across Academia, Business and Education and therefore help us understand how leadership fashions diffuse within the subsets and across Academia, Business and Education.

In order to identify clusters, we looked at compiled heatmaps that depict clusters and represent words that correlate with each other using a colour schematic. As for the visual representation, words are represented in different shades from dark blue to vivid red; a blue colour symbolises a low or non-existent correlation and red shows a high and strong correlation. On the below-shown extract of a heatmap, different so-called heat zones with similar colour (either red or blue) are shown and contrast each other representing different clusters with different degrees of correlation. Based on heatmaps like these, we compiled a list of words that constitute a cluster; meaning bundling words into a cluster that are in proximity of each other and that are represented in the same colour on the heatmap. Further down in our analysis, we then observe the development of the same clusters over time and clusters across the three different subsets of Academia, Business and Education.

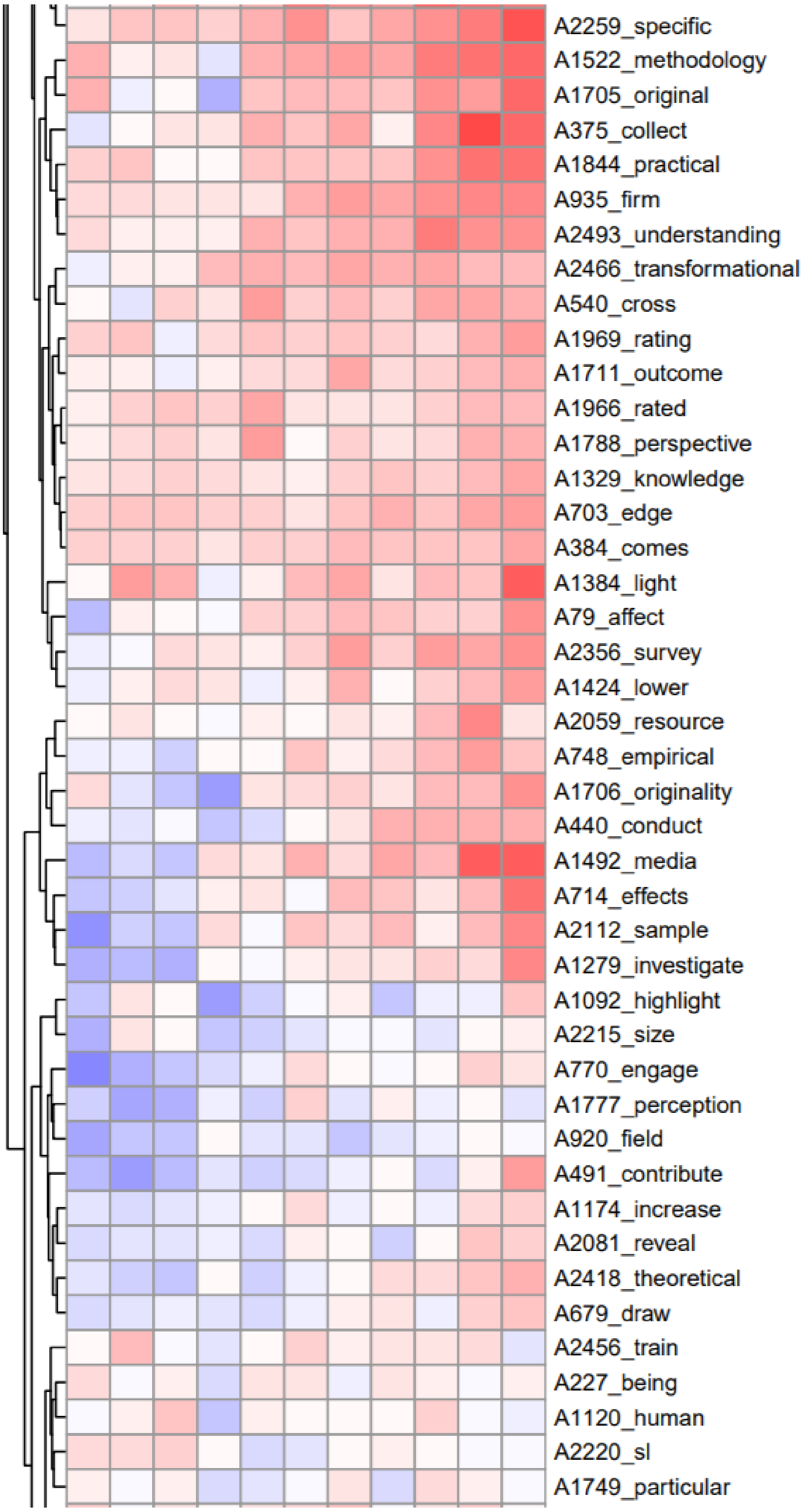

Figure 13: Extract of heatmap (here from the Academia subset)

5.2.1 Recording and analysing clusters

To understand why we are not looking at the full data sample of our subset called Academia, we need to discuss bias created by dominating words. We observed that the Academia subset features words with extreme high numbers of mentions that affect the representation of the whole sample in a heatmap. These words are words like leadership, leaders and leader (from now on referred to as *triple L words*) that have high explanation rates because they are mentioned in almost (if not) all abstracts of academic papers; especially because our Academia subset contains only the abstracts of articles whose topic has been categorised in the Leadership area. Words with extreme high amounts of mentions like the triple L words rightfully have high correlation values. They will have a relationship with almost any word from our sample because they are either mentioned in the same sentence or paragraph as the observed word or just because the triple L words are always used in conjunction with the word under observation. As these triple L words are the words that in regard to our sample have the highest explanation rates, they will be rightfully depicted with high correlation values (in vivid red), but at the same time depict the words with lower correlation values in the heatmap with less distinctive colours (in blue or light shades of blue). We were expecting that the triple L words would score very high counts of mentions and hereby have high explanation rates. Nevertheless, we wish to identify other relevant and determining words used in the leadership sphere that have high explanation rates (and hereby also having a high number of relationships) if not as high as the triple L words. Consequently, when these words are removed from the sample, they allow for other words with high explanation rates to become the extreme upper end of the correlation and also colouring scale. This does not change the explanation rate for each word; it juts changes the colour in which the word is represented in the heatmap. R, the application that we have used to create a printout of the different heatmaps, allocates the colour dark blue to the lowest explanation rate of the entire sample and the colour vivid red to the data point(s) with the highest explanation rate. Therefore, we can just remove words like the triple L words that dominate the heatmap due to their high explanation rates to balance out the colour scale for the correlation value within our subset. Removing these words does not change the respective explanation rate for each word; it just changes how colours are distributed among the lowest and highest explanation rate for our sample. Via this method we create more fine-grained clusters in the main body of the data sample that would otherwise just be represented in plain blue and not providing any insightful data on a visual basis. It would mean that we would otherwise see only a couple of words coloured in red and most of the rest of words coloured in any of the shades of blue.

These steps are not only applicable to the Academia subset, but they also apply to the Business and Education subsets, as we also found range-topping amounts of mentions for the triple L words in these subsets. This does not come at a surprise, because the data gathering RPA was in both instances programmed to capture every mention of "leader" and record the subsite to a predefined Excel file for every subsite where the criterion was true. Instead of only recording mentions of leadership, by choosing the string "leader" we could include a wider variety of mentions revolving around the leadership sphere, including leadership itself. This selection criteria on the other hand means again that the triple L words are found in the top quantile of the explanation rate scale by the nature of our data gathering design. In conclusion, our data gathering design made it necessary to gradually remove words from the observed sample in order to reduce the selection bias created by it.

In order to best determine and visualize the clusters within each subset, we gradually removed the highest correlating words to make room for lower-correlating clusters to appear in the visual representation. By removing words gradually from the heatmaps, we were able to incrementally determine clusters with lower explanation rates that correlated than for instance the triple L word clusters. We started by firstly removing the first 25% in volume of word mentions to see what difference in cluster constitution we could observe in this scenario. In the next step we removed another 25% in volume in most mentioned words to arrive at a total of 50% in volume of most mentioned words removed. The difference in how this impacts the visual representation of the respective heatmaps can be seen below in Figure 14. The boxes that are coloured on the left in a light blue shade to represent a higher explanation rate than the words surrounding them, become red and light red on the right depiction of the heatmap after we have further increased the removal rate of highest-mentioned words from 25% to 50%. We have consecutively increased the removal rate of words by intervals of 10% until eventually arriving at heatmaps depicting only 1% and 5% of remaining words, or in other terms leaving us with the 1% and 5% (still in volume) of words with the lowest explanation rates of the subset.

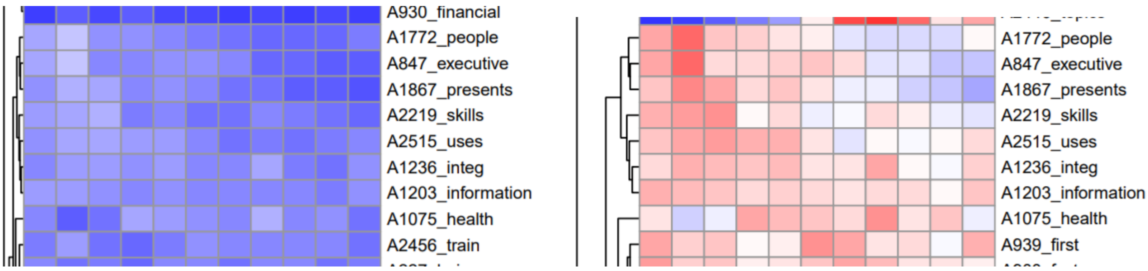

Figure 14: heatmaps within Academia; 25% of volume of most mentioned words removed (left) vs. 50% of volume of most mentioned words removed (right).

5.2.1.1 Academia

This series of graphs is intended to show how the explanatory capacity of each cluster varies over time within each subset. Therefore, for all the following graphs, the two axes represent the observed years on the x-axis and the aggregate explanation rate (in the following abbreviated with *AER*) on the y-axis. To determine the ordination point for each cluster per year, we make the sum of the explanation rates for each word that constituted that specific cluster per each year. As we do not only have one explanation rate per word and cluster but for each year of our observed time period, we can also determine if words and clusters showcase increases or decreases in their explanation rates over time. This also means to show if words have become stronger or weaker over time to explain the general vocabulary used in the Leadership domain.

Cluster	Words included in cluster
A1	care, challenge, group, including, key, member, mental, personal, presented, program, public, report, skill, vice
A2	actors, affect, aim, collect, comes, conduct, cross, discussed, edge, education, effects, empirical, firm, fit, further, however, investigate, knowledge, light, lower, media, methodology, original, originality, outcome, perspective, practical, rated, rating, resource, sample, self, specific, studies, survey, test, transformational, understanding, while
A3	best, direction, discussion, element, example, executives, fail, goals, governance, initiative, local, much, office, open, programs, rational, read, responsibility, setting, technology, traditional
A4	authentic, contributes, equation, female, indirect, jls, mechanisms, mediating, modelling, moderated, moderating, quantitative, reduce, regression, servant, teacher
A5	achieve, authors, cause, create, describe, difference, focuses, point, several, shed, successful, type, vision
A6	across, collected, companies, conducted, exist, face, grow, hold, mediate, positively, rise, sector, training, turn, working
A7	account, analyse, behaviors, benefit, conceptual, enhance, firms, followers, higher, innovation, insight, institution, interact, interviews, job, limitations, negative, perceptions, teams

Table 1: List of words included in analysed Academia clusters

In practical terms, if we look at the cluster A1 from Academia, we can state that the words in the cluster A1 accounts for approximately 1,5% of our Academia subset for the year 2008. We find the same information in the below-shown table that serves as the underlying data input for the Academia cluster graph shown in Figure 16. We find that the 14 words in cluster A1 can explain exactly 1,49161% of the word usage in our Academia subset for the year 2008 with the strongest contribution coming from the term "key" with an explanation rate of around 0,12% (see Table 2).

Another interesting observation we can make is to look at the values of the respective explanation rates for each word. Here, we find that most of the explanation rates are situated in the same value range. The reason behind this is relatively straightforward as the words would not constitute a cluster in the first place if their values would not be similar and interrelated to each other. We see the same in the heatmap in Figure 15 where the words of the cluster A1 are coloured in similar hues of red to visually show their belonging to the same cluster. It is worth to note that similar explanation rates are not a sufficient condition for words to appear in the same cluster. The words in the cluster additionally need to have strong enough relationship with each other. Besides the different colour hues to establish these relationships in a visual manner, the brackets on the left-hand side of the heatmap group words into very small clusters that in turn are grouped into bigger clusters again. It would not be meaningful to stick to the miniature clusters that often only contain a maximum of three words but look at the larger grouped clusters. This is what we have also done regarding the cluster A1 (and the rest of the clusters as a matter of fact) to look for a bigger cluster. If we trace back the tree of brackets from the words in cluster A1, we find that they all trace back to the same branch and therefore are interrelated with each making them belong to the same cluster A1.

Cluster A1	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
care	0.112791	0.0832	0.094331	0.116464	0.09922	0.1128	0.097233	0.099924	0.088837	0.094106	0.090485
challenge	0.094377	0.100017	0.112377	0.107505	0.109896	0.096593	0.087386	0.096269	0.113584	0.097592	0.09959
group	0.107037	0.129225	0.118939	0.103772	0.099848	0.102427	0.098463	0.093831	0.106604	0.092363	0.084225
including	0.105886	0.117719	0.111557	0.0978	0.109896	0.116041	0.10154	0.107845	0.099624	0.07726	0.079103
key	0.120848	0.108868	0.098432	0.098546	0.10236	0.097241	0.08554	0.087129	0.083761	0.09643	0.089916
member	0.11049	0.094706	0.106635	0.110491	0.104872	0.093351	0.088002	0.099315	0.117392	0.097011	0.105281
mental	0.101282	0.115949	0.081207	0.114224	0.106756	0.100482	0.095386	0.096878	0.090741	0.095268	0.091054
personal	0.113942	0.107983	0.098432	0.079136	0.096708	0.087517	0.091079	0.081646	0.082491	0.091783	0.088209
presented	0.078263	0.111523	0.103354	0.108998	0.109268	0.132896	0.115694	0.115157	0.109777	0.068546	0.082518
program	0.113942	0.104442	0.100893	0.107505	0.108012	0.095944	0.094156	0.09505	0.081857	0.079003	0.090485
public	0.087471	0.092936	0.09023	0.112731	0.081637	0.10891	0.107079	0.096878	0.101528	0.101658	0.098452
report	0.12315	0.097362	0.100073	0.10004	0.091056	0.094648	0.09354	0.097487	0.089472	0.076679	0.077396
skill	0.116244	0.115949	0.117299	0.087348	0.097336	0.085572	0.090463	0.093222	0.097086	0.081907	0.076258
vice	0.105886	0.087625	0.086128	0.09556	0.091056	0.100482	0.097233	0.104799	0.082491	0.098753	0.08707
Sum	**1.49161**	**1.467503**	**1.419888**	**1.440122**	**1.40792**	**1.424904**	**1.342794**	**1.365431**	**1.345246**	**1.248359**	**1.240041**

Table 2: Table of yearly ER in cluster A1 in the Academia subset summing up the AERs in %

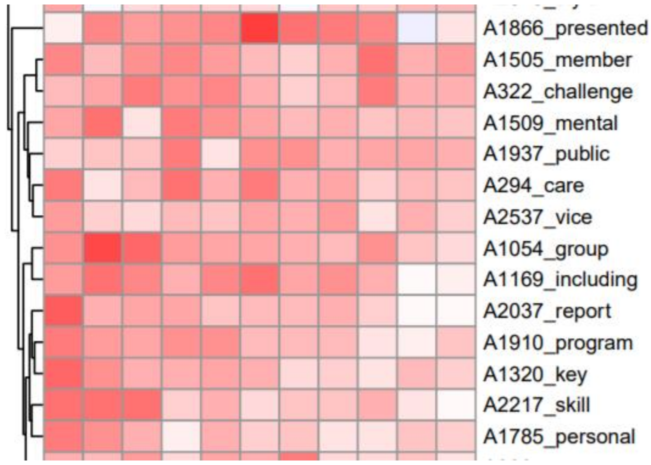

Figure 15: Extract of Academia heatmap around the words of cluster A1

When we look at the heatmap of cluster A1, we find that the word *group* in the year 2009 and the word *presented* in the year 2013 are coloured in the most pronounced shade of red representing the highest explanation rates out of this cluster. When we look at the numeric values in the table for cluster A1, we come to the same conclusion that *group* in 2009 has an explanation rate of 0,129225% and *presented* an explanation rate of 0,132896% in 2013. Both the data table and the heatmap provide the same image because they rely the same data; therefore, it should not come as a surprise that they draw the same picture. Some words are depicted in white for some years; e.g. the words *including* and *report* for the years 2017 and 2018. For these years, the words have explanation rates lower than 0,08% as we see from the data table. This also means that their explanation rates are considerably lower than for the years and words that surround them. A potential reason for this phenomenon could be that these specific words became less fashionable to use after the end of 2016 compared to other words in the cluster. They are the first words in that cluster that contribute to the decline in importance of this cluster to describe Leadership in the academic arena. We see this decline in the overall importance of the cluster also when looking at the vertical sums of the table and also in the way how the cluster is coloured in the heatmap. The AER for cluster A1 peaks in the year 2008 with approximately 1,49% and reaches its lowest point so far in 2018 with around 1,24%. This equals to a decline of 16,8% over the observed time period; in other terms, in 2018 the cluster A1 has been 16,8% less precise at explaining the general usage of word in an academic context compared to 2008. We see the same at glance when looking at the curve for cluster A1 in Figure 16 with its negative slope.

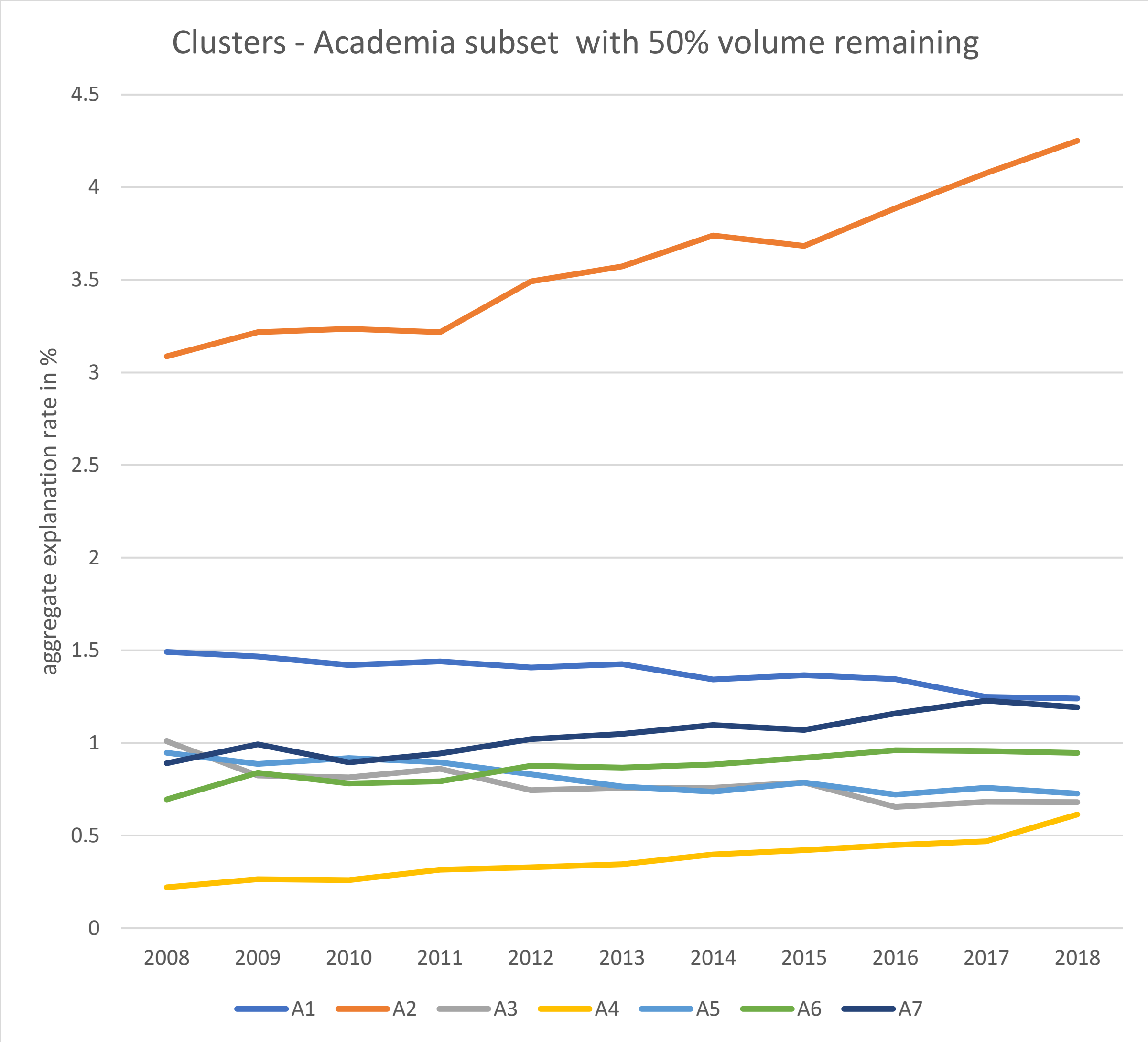

Figure 16: Graph of aggregate explanation rates for clusters in Academia subset (2008 to 2018)

The cluster A1 is although not the only cluster that we have as an observation to explain the vocabulary used in the academic Leadership sphere, but we have selected a total of seven clusters in our Academia subset. When we consider all seven clusters that we have selected in Academia, we notice that cluster A1 is not the only cluster that has a decreasing AER over the observed time period of our analysis. Considering Figure 16 above, we find that besides cluster A1 also the clusters A3 and A5 show diminishing AERs meaning that the importance of the words in these clusters in explaining Leadership reduces over time. As it is usually the case with fashions, where some clusters loose in importance, others gain in importance over time. We see that this is the case for the remaining clusters, namely the clusters A2, A4, A6 and A7 with the cluster A2 showing the highest absolute increase in AER; from about 3,09% in 2008 to around 4,25% in 2018 representing an increase of 1,16 percentage points in AER or in relative terms an increase of 37,7% over the observed 11 years. This increase of 37,7% for cluster A2 is although not the largest increase in relative terms as we find that cluster A4 encountered an increase of 177,9% from 2008´s explanation rate of 0,220979% to an explanation rate of 0,680628% in 2018. A general observation that we can make for the clusters on Figure 16, is that the curves of the clusters develop rather constantly and do not exhibit any abrupt changes in their trajectories. This reflects with what we have observed for the Academia subset in the NMDS plots in the beginning of this analysis. In the aggregate NMDS plot (Figure 9), we observed extremely high degrees in overlap of the Academia data points. Additionally, in the NMDS map that only plotted Academia data points (Figure 10), we have seen an almost linear arrangement of its data points. This coincides with the findings from the above graph comparing the clusters A1 to A7, where the graph (Figure 16) is characterised by the consistency of the curves.

Considering that some clusters gain in importance over time whereas others lose in importance, we are interested in seeing how our sampled clusters within the Academia subset evolve in their entirety over time. An easy and straightforward way to look at all the clusters is to trace how the vertical sum of the seven sampled clusters in Academia changes over the observed timeframe. We will name this sum the *aggregate explanation rate on a subset level*, forthgoing abbreviated with *AER*. When consulting the row named "AER" in Table 3, we can see that between 2008 and 2018, the sum of AERs of our sampled clusters increases from originally 8,34% in 2008 to 9,65% in 2018; 2018 is at the same time the sample maximum, but the year 2010 instead of the year 2008 is the sample minimum at 8,32%. This also answers our question that despite the fact that the AERs of some clusters increased and of others decreased, we can see a general increase in the Academia AER by 1,3 percentage points over the observed 11 years. All in all, this means that our selected clusters have in their entirety gained in explanatory capacity regarding the vocabulary used in the Leadership sphere. Furthermore, with subset AERs ranging from above 8% to close to 10%, we can state that these clusters are also representative (with some limitations) to the dynamics of vocabulary used in the academic literature covering leadership and that they are sufficient at drawing indications of how leadership fashions behave.

Cluster	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
A1	1.49161	1.467503	1.419888	1.440122	1.40792	1.424904	1.342794	1.365431	1.345246	1.248359	1.240041
A2	3.086803	3.217355	3.235147	3.216944	3.491541	3.572633	3.738531	3.6838	3.88535	4.076772	4.250512
A3	1.009369	0.824032	0.813708	0.860042	0.745406	0.759128	0.758783	0.785991	0.654856	0.683141	0.680628
A4	0.220979	0.264646	0.259205	0.316543	0.329059	0.346178	0.397546	0.421632	0.449896	0.469369	0.614045
A5	0.947218	0.88776	0.918703	0.895877	0.831439	0.764314	0.737244	0.785991	0.721483	0.758077	0.726724
A6	0.695164	0.839079	0.781718	0.792851	0.876653	0.868038	0.883093	0.919427	0.960709	0.956746	0.946392
A7	0.890822	0.993087	0.895735	0.943657	1.021715	1.048906	1.096636	1.071141	1.159957	1.228608	1.192807
AER	**8.341965**	**8.493463**	**8.324105**	**8.466035**	**8.703734**	**8.784099**	**8.954627**	**9.033414**	**9.177496**	**9.421073**	**9.65115**

Table 3: Table of yearly AERs for each cluster and aggregate explanation rates on a subset level (Academia)

5.2.1.2 Business

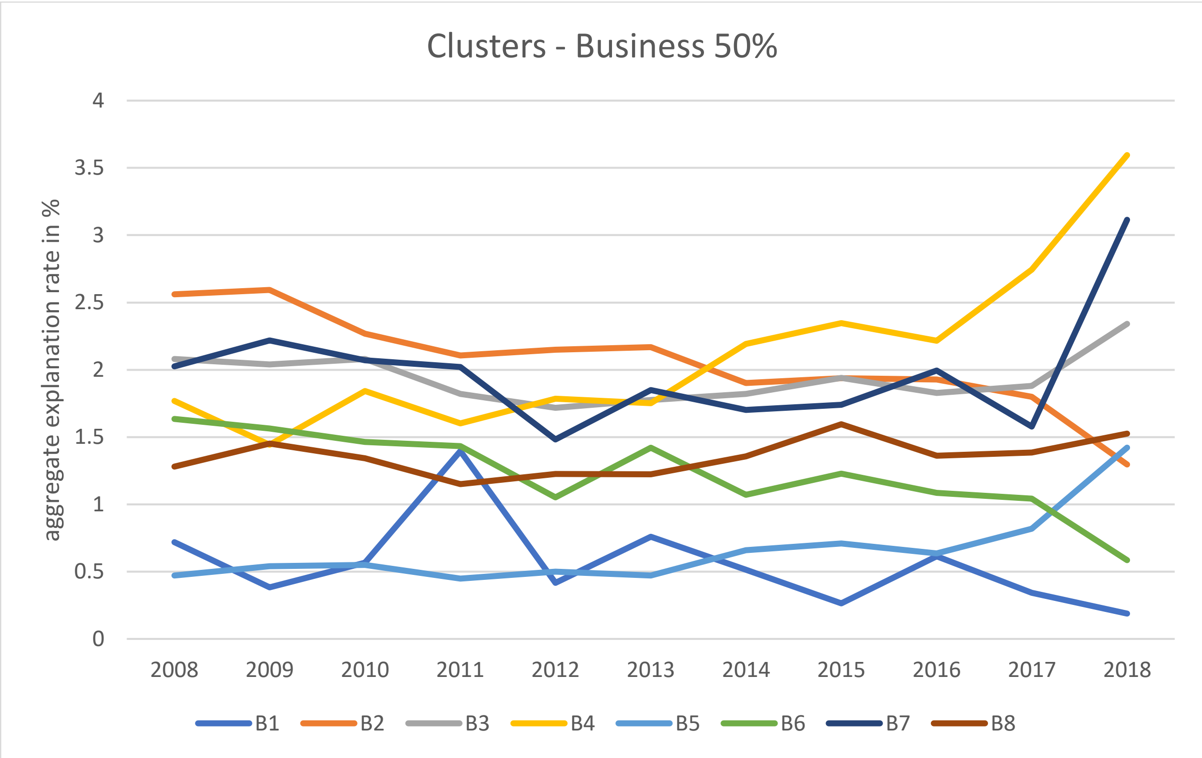

Figure 17: Graph of aggregate explanation rates for clusters in Business subset (2008 to 2018)

We have conducted the same steps of analysis that we conducted within Academia for the Business and the Education subsets. The first and obvious difference of the Business graph compared to the Academia graph is that the development of each cluster within Business is considerably less linear or coherent than what we have seen in Academia. Figure 17 shows that the curves in Business exhibit more pronounced peaks and lows which again correspond to what we have previously seen in the NMDS plots. The Business NMDS plot (Figure 11) showed already with its more dispersed data points that it will not exhibit the same linearity and coherence that we have previously seen with Academia. What especially draws our attention in Figure 17 is the spike of cluster B1 in the year 2011 which is completely out of line compared to the rest of the curve and indicates an overuse of the words contained in cluster B1 for that year compared to the rest of the sampled vocabulary; from the year 2010 to 2011, the cluster B1 increased by around 146% which is even more interesting because overall the cluster decreases by around 73% between 2008 and 2018. Possible reasons for this spike could be that either one website with a dominating amount of subsites changes the vocabulary used on its websites or that for the year 2011, many different websites change their content and hereby employ much of the words in that cluster B1 to construct their updated websites.

We see a similar outbreak with strong increases after 2016 for cluster B4 and after 2017 for cluster B7, exhibiting year-to-year growth of 24% to 31% for the cluster B4 and a year-to-year growth of 97% for the cluster B7. Beyond these pronounced increases of the clusters B4 and B7, we find also that the clusters B3, B5 and B8 experience growth after 2017. On the other hand, the clusters B2, B5 and B6 exhibit decreases from the year 2016 going forward. Consequently, an event or situation must have triggered this constellation where some set of words become more important and others have become less important. This is another indication for the existence of fashions in the Leadership industry and here more specifically in the Business environment of Leadership development consultancies and executive search firms.

Further, we see a higher degree of dynamism of the curves also reflected in the growth comparisons between the years 2008 and 2018 for all the clusters. The developments range as much as from -73,82% for cluster B1 and +201,45% for cluster B5, compared to a range of -32,57% to +177,87% for the Academia clusters.

Cluster	Words included in cluster
B1	interim, smurfit, solutions, solving
B2	candidate, consultant, day, direct, levels, officepostgraduate, others, professional, professionals, seek, shed, significance, specialist, used
B3	add, base, ceo, companies, focus, grow, mostly, positions, processes, resources, successfully, topic, yet
B4	across, assess, assessment, build, change, cross, ema, expertise, financial, formation, identity, roles, strategies, teamwork, thought, threat, understanding
B5	addition, ensure, hold, master, opinion, personality, Ronald, transformation, trusted, unit
B6	corporate, deliver, director, found, group, leads, non-profit, placed, recruitment, retained, via
B7	company, ddi, effect, effective, future, get, human, integ, members, owners, personal, planning, presidential, rights, served, sets, supported, times, variable
B8	based, industries, into, issue, longer, lower, networking, required, respect, skilled, sourcing, ten, ward

Table 4: List of words included in analysed Business clusters

When looking at the AERs values for each year in the Business subset, we come to two conclusions. The first one is the reflection of the increased dynamism of the Business subset in the variation of AER over the years starting at around 12,54% in 2008, hereafter reaching their lowest point in 2012 with an AER of 10,33% and reaching their highest percentage in 2018 at 14,07% (see Table 5). Contrary to the close to linear development that we have observed with the sample out of the Academia subset, we see here less coherent and more pronounced changes in the sampled clusters of the Business subset. Secondly, we find also in the subset's AER proof for the change in vocabulary used post 2016 with an initial slight decrease between 2015 and 2017 of 1,5% and an increase of 21,4% between the years 2017 and 2018. These numbers also show that the decrease of the clusters B2, B5 and B6 has been more than offset by the increase of the remaining clusters in these years.

Considering further the AERs from Table 5, we can argue that the sampled clusters with overall explanation rates between 10% and 14% are representative enough of the whole

Business subset and its vocabulary dynamics. These percentages even lie well above the AER scores for the Academia subset, although the Business sample contains one additional cluster compared to the sample from the Academia subset.

Cluster	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
B1	0.71852	0.383559	0.566861	1.395707	0.41686	0.758241	0.514459	0.264223	0.614987	0.342083	0.188127
B2	2.559727	2.593384	2.267445	2.106405	2.148431	2.168303	1.900444	1.936829	1.926865	1.798846	1.295987
B3	2.079217	2.039838	2.080072	1.820984	1.717319	1.77455	1.820574	1.939253	1.828015	1.880294	2.341137
B4	1.769355	1.442706	1.842892	1.60121	1.785014	1.750605	2.190953	2.346496	2.215648	2.743647	3.595318
B5	0.471529	0.54047	0.550259	0.448111	0.498806	0.470907	0.659322	0.710251	0.636169	0.819138	1.421405
B6	1.634633	1.564747	1.463403	1.432812	1.051056	1.420704	1.070419	1.229002	1.084524	1.042539	0.585284
B7	2.025328	2.218542	2.070585	2.020779	1.482168	1.849044	1.701551	1.740479	1.995354	1.577772	3.114548
B8	1.279863	1.451423	1.342441	1.150245	1.225639	1.223827	1.356229	1.595036	1.361303	1.384623	1.52592
AER	**12.53817**	**12.23467**	**12.18396**	**11.97625**	**10.32529**	**11.41618**	**11.21395**	**11.76157**	**11.66287**	**11.58894**	**14.06773**

Table 5: Table of yearly AERs for each cluster and aggregate explanation rates on a subset level (Business)

5.2.1.3 Education

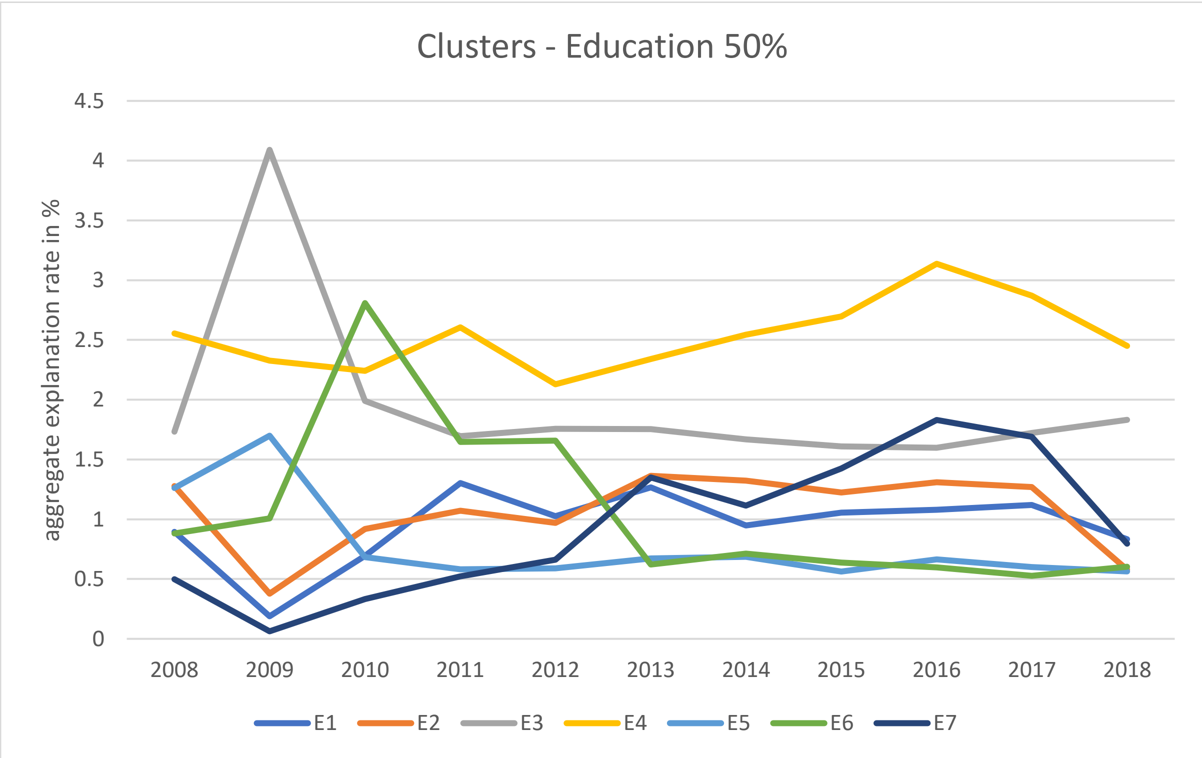

Figure 18: Graph of aggregate explanation rates for clusters in Education subset (2008 to 2018)

The last of the three subsets that we chose to include in our study is the Education subset where the picked clusters are graphically represented in the line chart in Figure 18. What becomes visible at first glance is that the Education subset has the highest degree of volatility represented with abrupt changes in how the cluster curves develop. The Education subset is completely missing the steadiness or linearity that we have previously seen with Academia and still in part with the Business subset. It is rather characterised by strong peaks and lows for most part until the year 2013. After 2013, the curves are less volatile and become slightly more stable with the curves of the clusters E1, E3, E5 and E6 exhibiting relatively flat curves.

A curious observation that we can make is the fact that five out of the seven clusters in Education exhibit either peaks or lows in the year 2009 hinting at that these lows and peaks for the same year might be somehow connected. One reason for this volatility could be explained by the fact that the clusters visible in the Education subset contain less words on average when we compare them to the clusters found in Academia or Business. When the amount of words contained in one cluster is on average lower, then the amount of mentions of each word have a stronger impact on the cluster as a whole. Where the clusters in Academia contained on average 19 words and in Business 12,6 words, a cluster in Education only contains 9,4 words on average making the Education cluster more susceptible to stronger changes with only one word changing. So, already the lower number of words per cluster can be an explanation for the volatile curves that we see on Figure 18. Besides that, we also found that in general the vocabulary in the Education subset is characterised by the lowest degree of overlap of any of the subsets in our Leadership dataset as shown in the aggregate NMDS plot (Figure 12). This lower degree of overlap means that the vocabulary used in the Education subset is less aligned and more differentiated compared to the other two subsets. This makes it plausible that a combination of both factors – a lower amount of words per cluster and the least consistent subset for use of vocabulary – is responsible for the higher degree of volatility in the Education subset.

Cluster	Words included in cluster
E1	ever, known, least, owners, personal, personality, sense
E2	add, class, dual, effect, effective, executives, individual, lower, others, roles
E3	change, end, environment, focus, makers, offered, thought, threat, undergraduate, up, used, washington
E4	career, challenges, come, help, here, impact, knowledge, linbeh, marketing, needed, provided, successful, taken, teamed, times
E5	become, developing, get, ranked, understanding, visionary, widely
E6	emerge, emerging, long, material, performance, performed, slides, small
E7	any, course, organizations, progress, training, trainings

Table 6: List of words included in analysed Education clusters

We wish to emphasise that also the nature of the words themselves have an impact on the volatility of cluster and consequently also on the subset. Depending on how deeply a word is embedded into the vocabulary of daily-use or not, the likelihood changes by which a word can be replaced by another word. More specialised vocabulary, in contrast to generic vocabulary, has a higher likelihood of being replaced by other specialised vocabulary; this being an indicator for the rise and fall of specific fashions. When we consider how sentences are usually constructed, we find that across sentences without regard to the context of the sentence, a standard set of words is repeatedly used to allow for sentence construction in the first place. If we disregard the words that constitute standard elements for a sentence, we can isolate the words that define the sentence's meaning. These are the words that we are interested in finding, because they are providing insights if words or groups of words drive a fashion. When considering Table 6 listing the words in the clusters of our Education subset, we come to realise that these clusters only contain few words that are somehow relatable to Leadership itself.

Cluster	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
E1	0.895742	0.188798	0.693132	1.302983	1.026527	1.268187	0.947777	1.056422	1.079886	1.120993	0.834492
E2	1.277533	0.377596	0.918174	1.072737	0.970627	1.363735	1.323071	1.225322	1.31036	1.268817	0.579509
E3	1.732746	4.090623	1.989378	1.695447	1.758309	1.754615	1.669741	1.610924	1.598454	1.722141	1.831247
E4	2.555066	2.328508	2.241426	2.605965	2.129281	2.340934	2.544367	2.696028	3.13743	2.870236	2.44939
E5	1.262849	1.699182	0.68413	0.580848	0.589491	0.673181	0.686979	0.564063	0.665403	0.601148	0.564055
E6	0.881057	1.006923	2.808534	1.648352	1.656672	0.621064	0.712423	0.637359	0.596632	0.527236	0.602689
E7	0.499266	0.062933	0.333063	0.523286	0.660636	1.350706	1.113161	1.424497	1.830787	1.690113	0.795858
AER	**9.104258**	**9.754563**	**9.667837**	**9.429618**	**8.791544**	**9.372421**	**8.997519**	**9.214615**	**10.21895**	**9.800685**	**7.65724**

Figure 19: Table of yearly AERs for each cluster and AERs on a subset level (Education)

Even though the year-over-year volatility of the Education subset is highly pronounced on our sample, we find that the 2018 over 2008 comparison numbers do not necessarily draw the same picture. Where the year-to-year variation for the clusters go could as high as +179% for cluster E6 from 2009 to 2010, the 2018 over 2008 comparison only exhibits growth or regressions that range from -55,33% for the cluster E5 to +59,41% for the cluster E7. This difference between the year-over-year variations over the ten-year variations indicates two things. Firstly, that despite the year-over-year volatility of the different clusters, the movements mostly equal each other out, meaning that the growth of some clusters is cancelled out by the regression of others. Secondly, when looking at the subset AERs for each year, we realise that, except for the year 2018, we cannot identify any major variations in the subset AERs over the years. They range between 8.79% in 2012 and 10.22% in 2016 with the year 2018 being the outlier at 7.66%. This provides additional proof for our suspicion that the growth of some clusters cancels out the recession of others indicating a negative correlation of some sort between different clusters in the same years. This in turn means again that we can also see fashions in our Education subset as some words' increased popularity dampens the use of other words.

Further, to verify the validity of the selected clusters from the Education subset, we consider again the subset AERs over the years to find AERs ranging from 7,66% to 10,22% that show that the sampled clusters can be representative of the Education subset and do not only represent a minor share of the subset. With this, we argue that due to our methodology, the sampled clusters within the three subsets are good at gaining an impression of the overall workings of each subset. Our analysis is not limited to understanding how each subset works and behaves individually, but also how the three subsets work with each other and if and how they are interrelated. In the following, we will dive into a cross-subset analysis of three selected words (*authentic*, *complex* and *transformational*) that should provide some insight on the interdependencies between Academia, Business and Education.

5.2.2 Clusters across subsets for specific words (authentic, complex, transformational)

After having analysed clusters within our three subsets, we experienced that the clusters that we have identified, do not necessarily contain the same words making it difficult to analyse the behaviour of words and groups of words across the subsets. So instead of just observing and analysing how the vocabulary within each subset develops, we picked three terms that are, following our understanding, representative of different paradigms in the Leadership sphere and observe how the clusters that contain these words develop. Selecting and observing the development of the clusters around these words is particularly important to track their development across Academia, Business and Education and thereby indicate the existence of leadership fashions. When we previously let the data talk and let the clusters naturally appear, were we unable to verify the existence of leadership fashions across Academia, Business and Education and the fashion setting role of academics. Our findings below partly indicate the existence of such leadership fashions across Academia, Business and Education but because of varying patterns of diffusion we question the role of academic scholars as leadership fashion setters.

The terms that we selected for these clusters are *transformational*, *authentic* and *complex*. We picked specifically these terms, because we know that these terms are specifically used in conjunction with leadership to describe different paradigms of leadership (transformational leadership, authentic leadership and complexity leadership). We are also aware that this creates bias, which we carefully considered when we chose these words instead of letting our dataset create relationships across the different subsets. We wish to emphasise that we also are aware that the third paradigm is generally referred to as complexity leadership instead of complex leadership, but we made a conscious choice of choosing complex instead of complexity as the term that we wanted to track across the three subsets. Only the term complex was found across all three subsets whereas the term complexity was not. Additionally, choosing three adjectives rather than two adjectives and a noun should also make the three terms more comparable. Further, by only picking adjectives, we can ensure that they are used in a similar manner in a sentence facilitating to compare all three terms and how they transcend.

In order to find the cluster that contain one of the three above-mentioned words, we proceeded in a similar fashion as when we determined the remaining clusters. In each of the subsets, we searched for one of the three selected words in the respective heatmap. When we found that word in the heatmap, we determined a cluster around that word by following the same colour coding technique as mentioned before. This means that we determined the clusters by registering every word that is in proximity and is coloured in a similar shade as our reference word. This methodology allows us to create "forced" clusters around the selected words, but it also means that the size of the cluster can vary by a considerable margin depending on how strongly a word correlates with other words in its proximity. We provide an example for this based on the clusters around the word *transformational*. In Academia we found transformational in a cluster with 38 other words, in Business with 24 other words and in Education only with four other words. This already shows that the size of the clusters can vary considerably in size.

The methodology of analysis is similar to the one that we applied for the analysis of each subset with a graphical representation of the explanation rates over time for each of the words across our three subsets. Here again, we represent the years on the x-axis and the explanatory rate of the respective cluster on the y-axis. Same as before, a positive slope represents an increased use of words in that cluster including the "standout" word and hereby potentially indicate a hike in importance of the standout word in that subset. A negative slope on the other hand indicates a loss in importance and may indicate a decrease in use of that term.

5.2.2.1 Investigating the diffusion of the word transformational across the three subsets

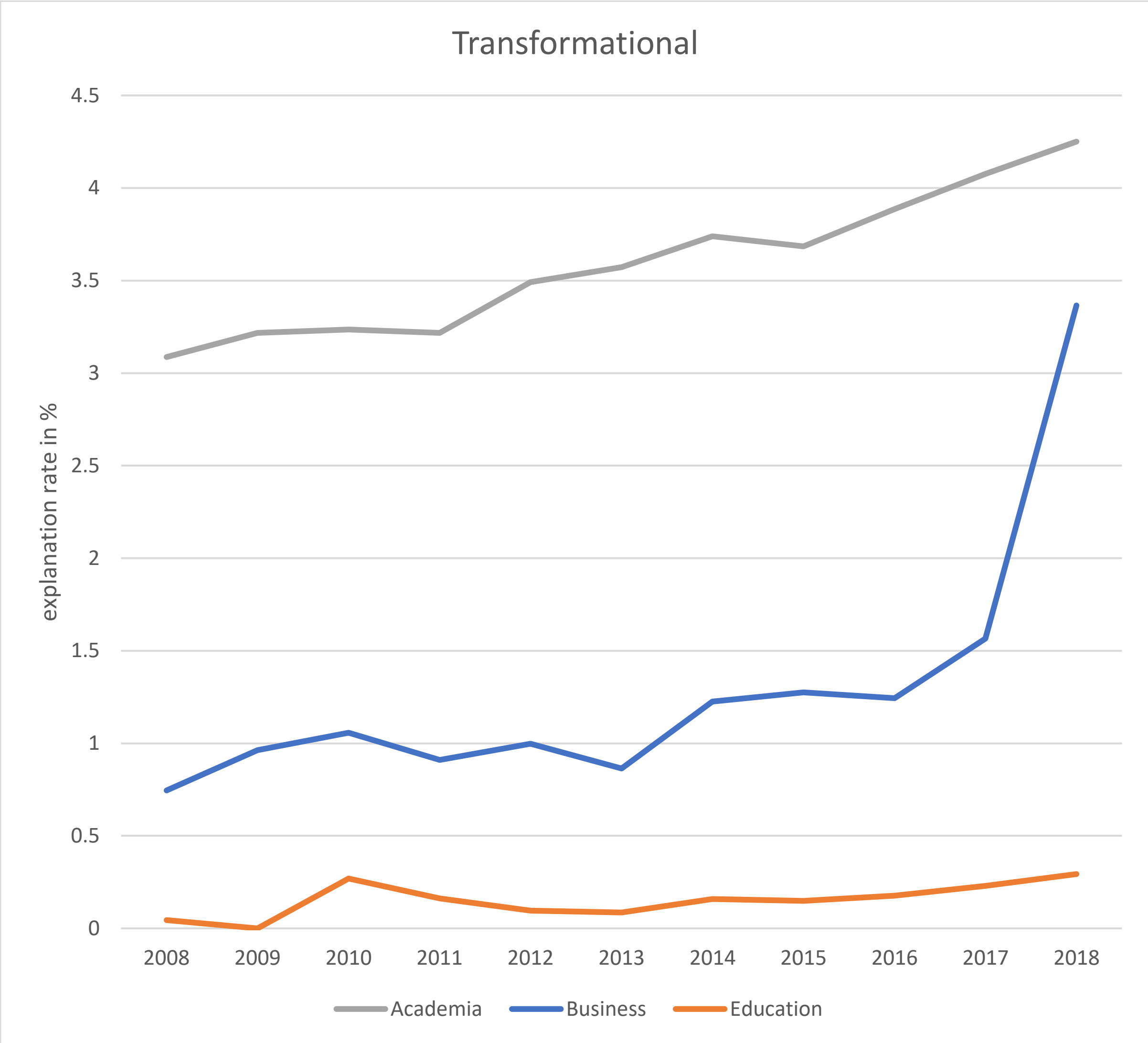

Figure 20: Clusters around key term transformational in Academia, Business and Education

Firstly, we glance at how the clusters around the three different words compare to each other in terms of respective explanation rates to create some context for the words. We notice that the explanation rate for the cluster around *transformational* is the highest of all three words that we manually selected from our data sample. *Transformational* reaches a peak in its explanation rate as high as 4,25% in 2018 whereas *authentic* only peaks at around 0,61% (Figure 21) and *complex* at approximately 1,4% (Figure 22). This comparison shows that the cluster around transformational is constituted of the most predominant clusters in our manually selected dataset.

We further see that the *transformational* cluster is by far the most used in Academia with a considerable distance to Business and Education subsets with an explanation rate ranging from 3,09% in 2008 to 4,25% in 2018 in Academia, partly due to the fact that the cluster is constituted of 39 words in Academia opposed to 25 words in Business and only five words in Education. Therefore, Education also exhibits only low explanation rates for the cluster that never exceed 0,3% and even dips to 0% in 2009. Education also shows an odd development as it adopts a parabolic development between 2010 and 2018 where it at both times comes close to 0,3% for its explanation rate. We also see the peculiar development of the Education subset in 2009 reflected in the graph of Figure 20. Where we have previously seen that for that year the Education subset exhibits peaks for some clusters and slumps for other clusters, we see here another slump of the Education curve resulting in the only record where the cluster around *transformational* reaches an explanation rate of 0%. In other terms: for the year 2009, *transformation* and the other words in the cluster are unable to provide any explanation for the vocabulary used within the Education subset. Moving on from the curious development of the Education curve, we can observe highly positive slopes of the Academia and Business curves, representing both considerable increases in the respective explanation rates and a boost in importance in both subsets. The Business subset registers also the highest climb for the cluster at an increase of +351% between 2008 (0,75%) and 2018 (3,37%) signifying that it has become much more important at describing leadership in a Business context. An especially strong increase in the Business subset can be observed from 2017 to 2018 with an increase of 115% for that year alone. This should nevertheless not take the focus away from its development in Academia, as the cluster around *transformational* has also gained here in popularity when we compare the years 2008 to 2018. Even though the cluster started out very high at slightly over 3% explanation rate, it continued to climb to its maximum at 4,25% in 2018 providing a considerable positive development over the observed timeframe.

All in all, we can argue that the cluster around *transformational* has become widely more popular in all three observed subsets with the strongest hike in the Business subset. We can further infer from the graph in Figure 20 that the popularity of the term *transformational* (when considering the respective clusters) transcends in a specific fashion between the three subsets; it started at some point prior to 2008 in Academia and found then its way to Business in order to finally find use in the description of MBA programmes of our Education subset. It is interesting to see that initially in 2008, the Business curve has been closer to the Education curve and that towards the end of our observation period around 2018, the gap between Academia and Business has closed down considerably approaching these two curves closer to each other. We can think of this development in a way that the transcendence from Academia to Business has accelerated over our observation timeframe but left the speed of transcendence into the Education sphere completely unaffected resulting in a gap that has grown over the observation timeframe between Business and Education.

We will have to see if this pattern also replicates for the other two that we want to examine more closely to verify the transcendence across subsets.

5.2.2.2 Investigating the diffusion of the word authentic across the three subsets

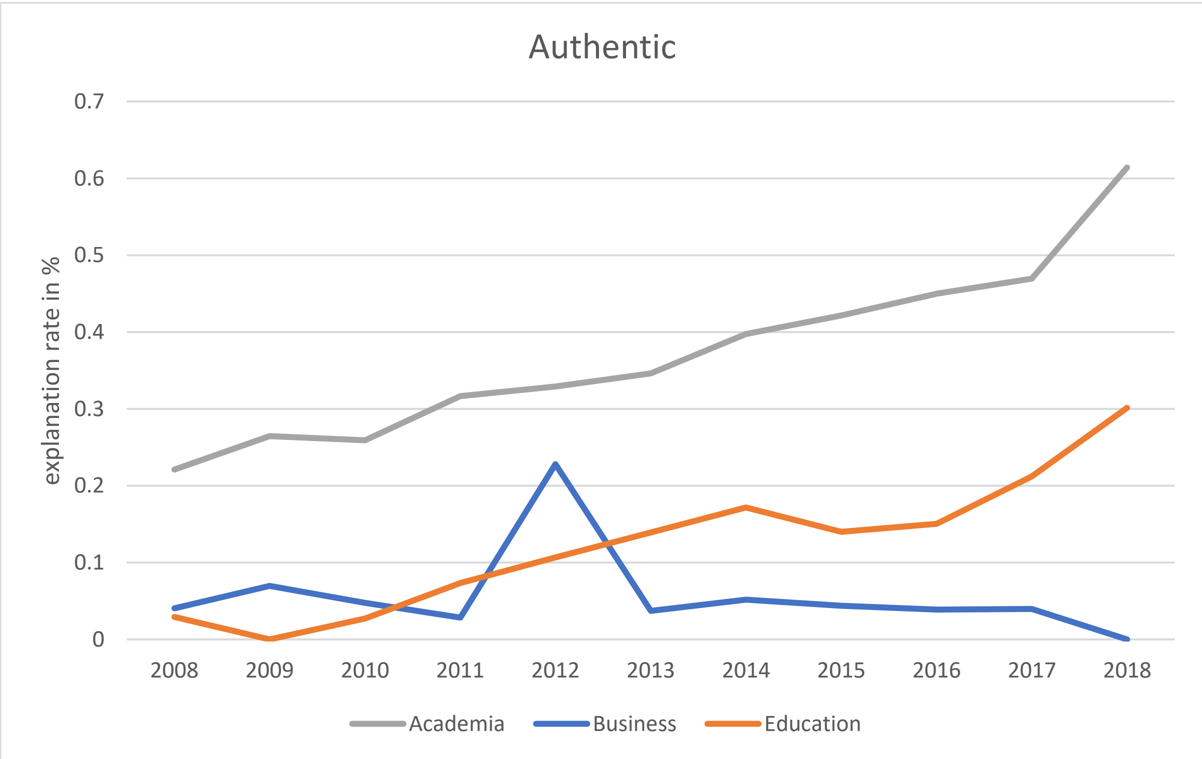

Figure 21: Clusters around key term authentic in Academia, Business and Education

Moving over to the cluster around the word *authentic*, we are presented with a different picture as compared to Academia. We immediately recognise that we have no longer the transcendence pattern that we saw with the *transformational* cluster. Instead, we see that the Business and Education curves are intersecting each other at three points, thereby nullifying our assumption established in the previous section that a universal way of transcendence for leadership paradigms exists.

It nevertheless remains unchanged that Academia is the dominating curve being clearly separated from the Business and Education curves. This signifies that the Academia cluster around *authentic* showcases the highest explanation rates of the three subsets. We further attest a constant and steady growth of this cluster by outlining a growth of +178% between 2008 (0,220979%) and 2018 (0,614045%). The dominance of the Academia subset for the cluster around the word *authentic* in part validates our assumption that the spread of new Leadership paradigms finds its origin first in Academia. For the clusters around *authentic*, we have also more comparative cluster sizes for the three subsets with 16 words in the Academia cluster, 14 words in the Business clusters and 12 words in the Education cluster. The development of the Academia curve is even more pronounced for *authentic* than it was for *transformational* which already had a high explanation rate at the beginning of our observation period.

Based from what we have observed in the *transformational* clusters, we would expect the Business curve to be situated between the Academia and Education curves. As Figure 21 shows, we find that the Business curve intersects on three occasions with the Business curve and is situated for the years 2008 to 2010 and 2012 over the Education curve; for the rest of the observation period, the Business curve is situated under the Education curve on y-axis. These are not the only particularities that the Business curve exhibits. Firstly, they Business curve peaks in the year 2012 elevating it completely out of its otherwise mostly negative development. Secondly as just mentioned, the Business curve has a negative slope meaning that the words in the *authentic* cluster have become less important in explaining the developments of Leadership in Business over time. This also contradicts our initial assumption that fashions transcend from Academia to Business and then to Education.

Another reason must exist that can explain why this cluster has a negative development in the Business subset.

Lastly, the Education curve which exhibits the exact same slump in the year 2009 that we have previously seen in the *transformational* clusters. It is another indication that a specific particularity in the Education subset is at the origin of this development. Let's remember Figure 18 in the Education section showcasing different clusters in the Education subset where we have observed that for the year 2009 all the clusters either reached a high or a low which is highly uncommon. Otherwise, it is easy to see that besides the slump in the year 2009 the Education curve exhibits a positive development over the observed period. Between 2008 and 2018, the cluster in the Education subset grows by an immense +926% due to a marginal comparative explanation rate in 2018 of only 0,02%. Otherwise, the developments of the Academia and the Education curves are relatively similar between 2008 and 2018, allowing us to cautiously claim that some dynamics of transcendence between Academia and Education, that we have previously seen in the *transformational* cluster, still exists.

We will have to see what patterns of transcendence are outlined in the last of the three word clusters that we have selected and to deduct from this any recurring typologies that allow us to state a universally applicable method in which fashions in Leadership develop over time and across subsets.

5.2.2.3 Investigating the diffusion of the word complex across the three subsets

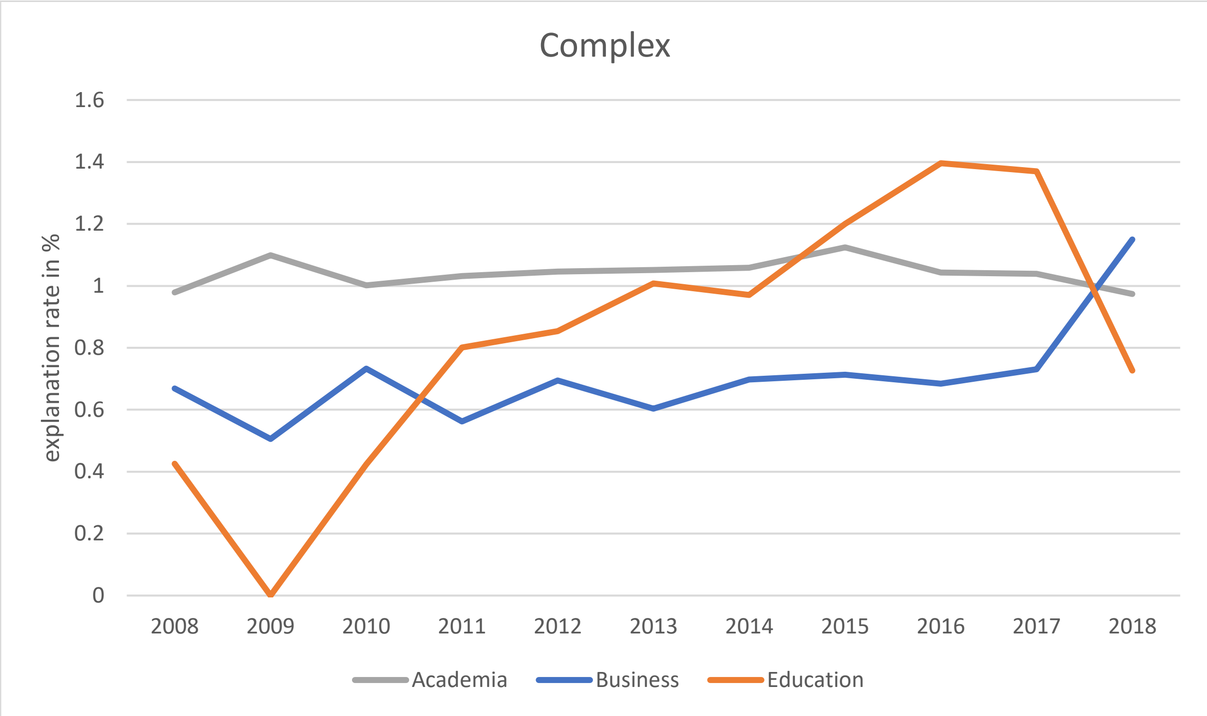

Figure 22: Clusters around key term complex in Academia, Business and Education

The graph in Figure 22 depicting the three clusters around *complex* draw a completely different picture from *transformation* and *authentic* with no clear-cut hierarchy between the three subsets that we saw previously. There is one thing that also persists with the *complex* cluster and that we have also seen in the two previous word-derived clusters, namely that for the Education subset the curve reaches its low at 0% explanation rate. In this case the Business curve appears to mirror to an extent the movements of the Education curve. Past the year 2009, the development of the Education curve becomes less clear-cut than in the other cases exhibiting a strong growth until 2016 and a considerable decrease in the year 2017 and especially 2018.

It becomes also clear that our previous assumption regarding the transcendence of trends is proven incorrect or at least not valid in every constellation. This constellation provides us with an example where each of the curves is for a different timeframe the dominating curve, leaving us unclear what order of transcendence between Academia, Business and Education exists. For most of the observation period (from 2008 until 2014), the Academia curve dominates the other two, with the Education curve taking over the lead in the years 2015 to 2017 and eventually the Business curve exhibiting the highest explanation rate of the three subsets in 2018. What is further interesting to see is that all three curves share a single intersection point between 2017 and 2018 which we haven't seen before. The Education curve of the *complex* cluster is by far the most volatile cluster with explanation rates ranging from 0% at its minimum in 2009 to a maximum of 1,40% in 2016.

The Academia cluster in contrast shows the least movements of all the Academia curves for the three manually selected word clusters, starting and ending in 2008 and 2018 respectively with almost the exact same explanation rate of around 0,97%. Also, for the remaining years, the Academia curve does not show any particular developments by barely exceeding 1,1% in 2015. This contrast strongly with the behaviour of the Academia curves that we have seen for the *transformational* and *authentic* clusters. An explanation for this phenomenon can be that the correct name of the third leadership paradigm is complexity leadership instead of complex leadership. As we argued earlier, we chose complex over complexity for a better comparability between the terms even if it means that we are not capturing all mentions of said paradigm. This is even more true for Academia that emphasises the correct use of terminology. For the remaining part, there is not a lot of insightful observations that we can derive from the Academia curve for the *complex* cluster.

The Business curve of the *complex* cluster is also characterised by ups and downs for most of the observation period, namely between 2008 and 2017. It is only for the year 2018 where the curve shows a strong increase and breaks out of the previously set outer boundaries of its consecutive ups and downs. For the rest, there is not a lot of valuable insights that we can gather from the Business curve on its own. Nevertheless, it is interesting to note that in terms of number of words that constitute the respective clusters, the three *complex* clusters are the closest to each other from the three manually selected words with 15 words for the Business and Education cluster and 17 words in the Academia cluster. This does not mean the words inside each of the clusters are the same, but it means that they comprise a similar amount of words and making their developments less influenced by the differences in amount of words per cluster.

5.2.2.4 Conclusion of the cluster analysis

In order to conclude our findings, we will run through our findings that we gathered so far. The Academia subset is very consistent in its development showed with clusters that either consistently climb or fall, indicating the presence of fashions and the focus of different groups of words depending on the year. We cannot observe abrupt changes from year to year making it the most consistent of our datasets. The subset AERs further show that we observe a general rise of interest in leadership in the Academic subset while at the same time registering that the declines of explanatory capacity of some cluster is more than compensated by the clusters with increasing explanation rates.

Turning to the next subset, we see less coherency and consistency in the Business subset compared to the Academia subset. It is also interesting to see that most clusters of the Business subset peak in 2018 after exhibiting volatile year-over-year developments that more often than not have consecutive growth and decline phases. Besides the year-over-year fluctuations, we further observe starker changes between 2008 and 2018 than those that we have seen in Academia. Additionally, the subset AER for Business also reflects two facts of the subset; firstly, the variation of the subset AER provides proof that the clusters are much more volatile than those in Academia and that language changes in Business happen more often and more pronounced. Secondly, a change of vocabulary in Business can be identified in the years following 2016 with a sharp increase in subset AER caused by the overcompensation of gaining clusters over losing clusters, indicating a change in vocabulary for said time period.

Lastly, the Education cluster are exhibiting the highest degrees of volatility of all three subsets resulting in the lowest degree of consistency in language. This means that language changes happen most frequently here and often these changes are quite radical. We further see two different sections on the graph; the years until 2013 that are extremely volatile and the years after 2013 that gain some steadiness and are less volatile. This volatility can also be caused by the fact that Education is the subset with the lowest number of words per cluster when compared to Academia and Business. Although we see strong year-over-year variations in the cluster, the 2008 versus 2018 comparison offers a different picture by exhibiting much lower degrees of variation over the entire observation period.

We also want to quickly summarise our finding in the word-based clusters of Academia, Business and Education. Based on the observations from the Figures 20 to 22 for the clusters around one specific leadership paradigm, we are unable to determine one universally valid way by which a specific paradigm transcends between our three subsets. This also means that there is no single leader/frontrunner in setting fashions with new leadership paradigms and driving their spread to other areas related to leadership research and development. We were hoping that when we focus on the same word(s) across subsets, we would be able to identify a clear hierarchy between the three subsets that would indicate that a general way of transcendence between the three subsets would exist.

Initially when consulting the *transformational* clusters, we were assuming a lead by Academia that would gradually drip down to Business and then Education. When we advanced to the *authentic* clusters, part of our assumption was already disproven as the Education curve was for a majority of years above the Business curve indicating that not in every instance a fashion first reaches the Business subset and then only the Education subset. We were still assuming that Academia would be at the origin of every new paradigm and that a fashion setting movement would be initiated from Academia. The third and last set of clusters (the *complex* clusters) voided also our rephrased assumption that Academia could be seen as the fashion setting entity. This was only partly true for some of the years of the *complex* clusters, meaning that we cannot say with certainty that a fashion setting movement always starts with Academia. We need to see that fashions setting process more differentiated than we were expecting.

Because we are unable to identify a clear and recurring pattern of diffusion along Academia, Business and Education in Leadership, we wanted to verify if another area/subject area would behave in the same way. For this sanity check we specifically chose the area of Management for its proximity to Leadership in terms of subject matter. This caught our interest in verifying if Management offers a clearer picture of fashions and they manner in which they diffuse. To maintain comparability to Leadership, we set the exact same criteria from the Leadership dataset for our Management dataset.

5.2.3 Comparison Leadership with Management to discover fashions

As previously said, leadership and management are conceptually close and even sometimes used interchangeably despite clear distinctions between both paradigms in an academic and professional setting. Therefore, we have argued that our method to determine leadership fashions and its diffusion can also be applied with the same methodology to management fashions as the areas are very close to each other and are to an extent interrelated. We see the closeness of both areas also with Guthey's model fashions that shares many elements with Abrahamson's management fashion setting model.

We wanted to see how differently management and leadership behave when the parameters for dataset construction are the same and to see if Management offers a clear manner of diffusion across subsets, something that our Leadership dataset has failed to deliver. To gain an initial sense of which differences we should expect between both, we drafted a Google Ngram for both the mentions of management and leadership in books that have been digitalised by the Google Books programme and having been published originally between 1900 and 2008. The result can be seen in Figure 23 plotting both curves of total mentions on a percentage scale for the observed timeframe. It needs to be noted that information on Google Ngram is only available until the year 2008 and thereby we were unable to compare the Ngram for the same years as our research design. Nevertheless, the timeframe shown in the Google Ngram is sufficient for showing a massive wave of interest in Management after 1970 where the two curves start to grow apart from each other. Where the leadership curve remains relatively stable after 1970, the management curve does not stop climbing until the mid-2000s where the management and leadership Ngrams exhibit serious hits and the popularity of both areas shrinks. Some event must be at the origin of the dent in the diffusion of Management and Leadership literature triggering their simultaneous decrease. A possible reason could for this could be the financial crisis around 2008 that slows enthusiasm of book publishing due to the difficult economic situation across the globe.

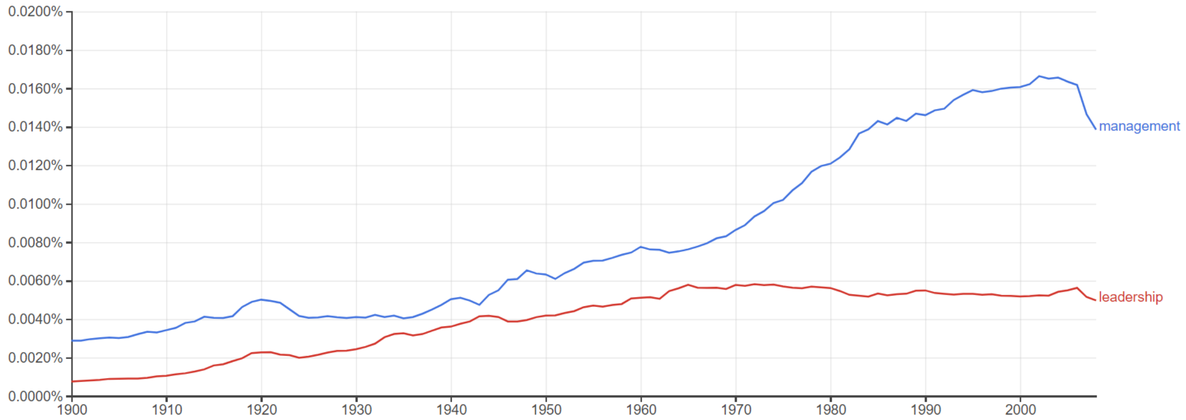

Figure 23: Google Ngram of mentions of Management and Leadership in digitalised literature 1900 to 2008 (Google Ngram, n.d.)

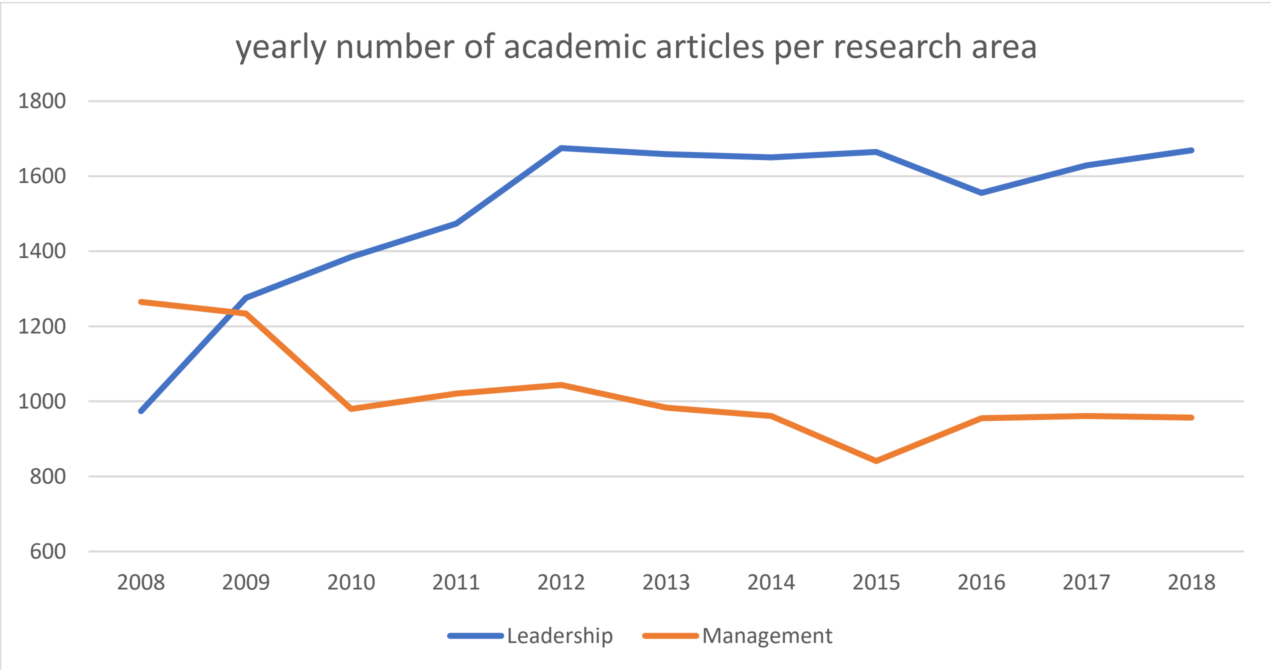

Figure 24: Graph with number of academic articles per research area and per year

It is interesting to compare the number of abstracts that we gathered for leadership and management in Academia and compare these to the numbers provided in the Ngram from Figure 23. The last Ngram record is captured for the year 2008 and shows a decline in both leadership and management mentions in books. This is the year that our study of leadership and management fashions starts. Towards of the Ngram we see a sharper decline in management mentions in books compared to the decline in mentions of leadership in books. Our data can confirm this trend also for academic research as reflected in our graph of Figure 24 that shows the number of academic articles in leadership and management between 2008 and 2018. In 2008 the number of articles for leadership was considerably less than the number of management articles for the same year. The situation already changes in 2009 when the number of articles published in the leadership domain marginally exceeds the number of articles publish that have management as their central topic. For the years after 2009, the gap between the number of articles in leadership and management grows steadily larger between both research domains. We see the biggest gap between the number of articles in leadership and management in the year 2015 where we count 1.665 articles in leadership compared to 841 publications in management, meaning that there is close to double the number of publications in the leadership domain compared to the publications in management for the same year. Overall, we clearly see the number of academic publications in leadership steadily climb (+71% for the period between 2008 and 2018) during our observation period whereas the number of management publications for the same timeframe decline at a similarly steady pace (-24% for the same period between 2008 and 2018). It is further interesting to see that the number of leadership articles has already reached its peak in the year 2012 and that it never really exceeds that level despite some variation in years that follow. This could indicate that it is sort of an artificial limit for the number of articles that make to publication every year; in other terms, that the output of all academic journals covering leadership topics has an upper limit driven by their journal's capacity. Another more important indication that we can derive from the graph in Figure 24 is the growing gap between the articles published in leadership and those published in management. The growing gap might indicate that scholars increasingly change from researching management to leadership because the management domain might be exhausted. This is in itself is a fashion because it could be an indication that some areas of research in their entirety might become less interesting to be investigated and studied and that scholars are therefore moving to other areas that are less crowded and less investigated. Other studies with a different scope from our study would be necessary to further investigate this specific situation and thereby cover a high-level fashion research across multiple focus areas (e.g. across leadership, management and others).

We found a similar picture to the Ngram (Figure 23) shown above when determining the limits of our Management dataset created for comparison. If we choose the exact criteria as we have for Leadership in the Business Source Complete academic database by only changing the topic selection from Leadership to Management, we would reach a data sample of 170.000 abstracts representing about 10 times as many academic articles as we have in our Leadership Academia subset. By selecting *people* as another keyword we reduced the dataset size from around 170.000 abstract to about 11.202 abstracts. With this example alone, we already note that Management is a more popular domain in academia than leadership, something already reflected in the above-shown Google Ngram. This difference should be kept in mind when we look at the following comparisons between leadership and management.

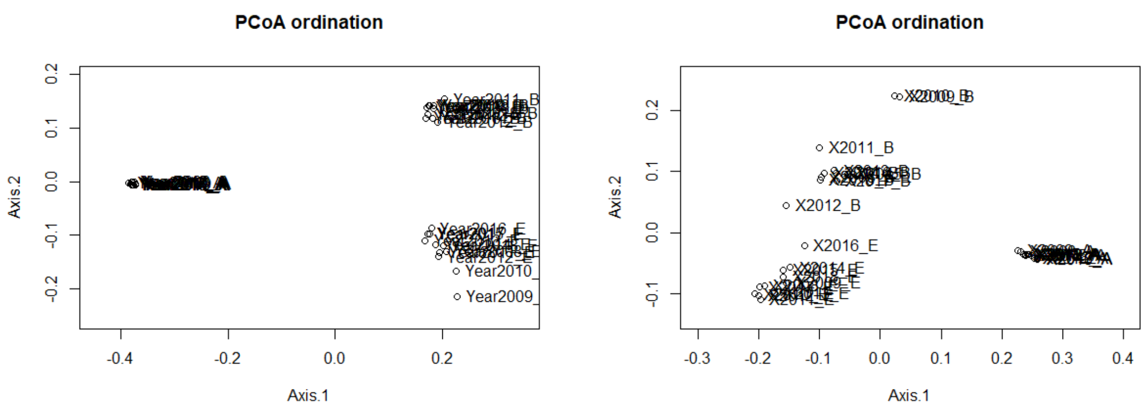

Figure 25: NMDS plots all subsets for leadership (left) and management (right)

When comparing the NMDS plots with the three subsets for Leadership on the left and Management on the right, we come to realise that the spill over between each subset is higher in the left Management NMDS plot compared to the Leadership NMDS plot on the left. This means that in Leadership the language in each of the three subsets is more segregated from another than in Management. This segregation may be a reason for our difficulties identifying patterns of diffusion across the three subsets in Leadership. It also means on the other hand that the language used in the three subsets of Management is closer to each other than in Leadership, potentially facilitating the diffusion of the same language and hereby fashions across Academia, Business and Education. Furthermore, we see that all three subsets are not pushed to the outer limits of the NMDS ordination map in the Management plot compared to the Leadership plot. In the Leadership plot, the three subsets are pushed close to the corners of the plot, whereas in Management they move slightly closer to each other and the centre of the ordination map.

We still see for Academia in Management that the overlap of the ordination points for each year have extreme high degrees of overlap; something that have previously seen in the overlap of the Academia ordination points in Leadership. Both Leadership and Management have this in common, although it is marginally less pronounced in Management. We can nevertheless derive from this that Academia exhibits a strong uniformity in language that we cannot observe in the other two subsets. As we previously mentioned, we expect this to be a consequence of the strict language criteria that are required for publishing an academic article. Whereas Business and Education have a lower degree of overlap but still being visually apart in Leadership, the same subsets are characterised by a lower visual separation in Management. Especially the year 2012 in Business and the year 2016 in Education appear visually close to each other. Hereby, we can say that the language used in Business or Education is more likely to be picked up by another subset respectively.

Despite the fact that all three subsets approach each other in Management, they still preserve their visual epicentres around which the subset's ordination points are organised. This translated into a somewhat different language between each subset that we already have encountered in Leadership. It nevertheless signifies that the diffusion should be facilitation to the approaching of the subsets.

We will have to see how the clusters in each subset behave beyond the overall NMDS plot that we have just analysed.

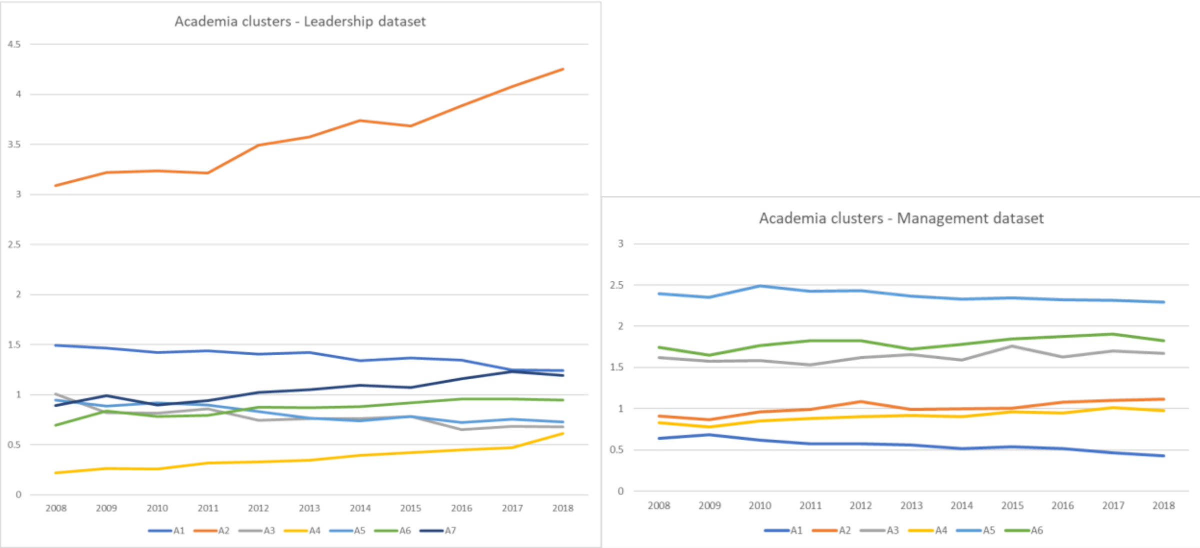

Figure 26: Academia clusters for leadership (left) and management (right)

We firstly compare the Academia clusters of Leadership on the left and Management on the right. We see that for most clusters no major difference between Leadership and Management can be found, except cluster A2 in Leadership which exhibits a clearly positive slope. For all the other clusters, we are unable to detect any meaningful differences between both paradigms. This indicates our assumption that language in the academic realm is monitored and limited explaining that the Academia clusters fail to show any major jumps or drops in the explanation rates of their clusters. For the Academia clusters in Management we see only minor variations and some clusters like A3 and A6 have around the similar explanation rates in 2008 as they do in 2018.

We fail to see fashions in the way where some clusters gain in popularity where other clusters in the same time lose in popularity signifying that fashion in the classic sense of term are hard to identify in the Academia subset of Management. It is although a similar development that we have observed with Leadership and therefore we must assume that this behaviour is symptomatic for Academia as a whole.

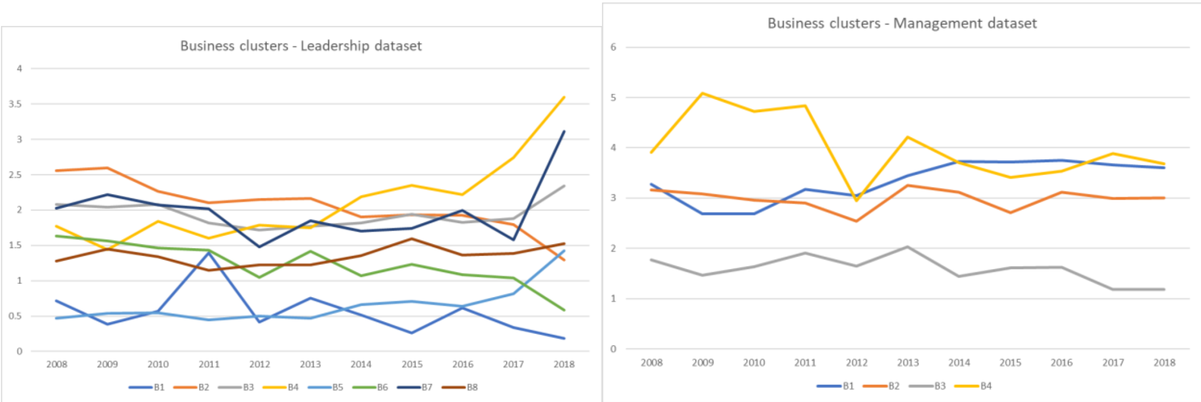

Figure 27: Business clusters for leadership (left) and management (right)

The Business clusters of Management (on the right plot) show a different and more dynamic picture. These curves are characterised by stronger variations over the observation period. For one we see a negative trend for most curves in the year 2012, something that we can in part also see with Leadership in 2012. Potentially an event across Academia is at the origin of this slump for the year 2012 as we are able to see this development in the Leadership and Management paradigms.

It is interesting to observe that the cluster B4 in Management exhibits high levels of dynamism, but it also comes close to its original explanation rate from 2008 in the last year of our observation in 2018. This also somewhat applies to the clusters B1 and B2 in Management which both have close to each other "start" and "end" values. Only the cluster B3 closes with a noticeably lower explanation rate in 2018 compared to its initial value from 2008.

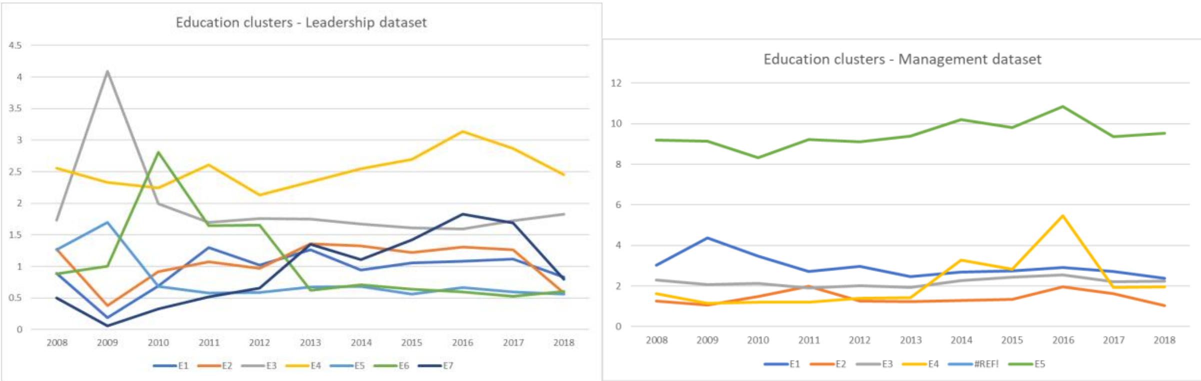

Figure 28: Education clusters for leadership (left) and management (right)

Lastly, when considering the Education cluster graphs for Leadership (on the left) and Management (on the right), we firstly notice the extremely high explanation rate of the cluster E5 in Management peaking at around 11% in 2016. This is by far the highest explanation rate that we have seen for any of the clusters in our datasets. We further see that the clusters E2, E4 and E5 of the Management dataset show spikes of different intensities in the year 2016; the clusters E1 and E3 only show a minor increase for that same year. This indicates that a trigger of some sort is potentially at the origin of their combined spikes. The Academia dataset shows a different picture for the year 2016 with only the clusters E4 and E7 exhibiting spikes and the other clusters remaining more or less flat for that year. This could mean that this special occasion triggering the spikes in the Education dataset is also specific to only the Education dataset.

Despite this very high explanation rate exhibited by the cluster E5 in the Management dataset, we also see with this cluster that its start and end values in 2008 and 2018 respectively are close to the same percentage meaning that overall its development over the observation period evens itself out. The cluster E4 exhibits an even stronger volatility especially in the years 2013 to 2017, but also here we conclude that all these developments over the observation period are cancelled out as the explanation rates in 2008 and 2018 are close to the same. This seems to be particular to the Education subset in the Management dataset being a subtle first indication for the fact that the fashion cycles in the Education subset might be of a shorter duration than previously assumed.

5.3 Discussing the key findings of our study

Through the use and analysis of big data, we provide a clearer understanding and a more precise analysis of leadership fashions and the diffusion of leadership techniques. The big data techniques that we utilised to analyse clusters of words and word usage do neither indicate the diffusion of leadership fashions across academic, business or educational contexts, nor does it confirm the role of academic scholars as leadership fashion setters. Our big data techniques are further unable to deny the existence of leadership or management fashions altogether and they call into question the ways that researchers have studied them previously and provide an outlook for new methods to further research these topics in the future.

We will first revisit important elements of the existing literature before we discuss our findings that we presented previously in our analysis and show where our big data-driven method adds to the previous research on leadership and management fashions. This is even more important because it allows us to show where our method exceeds the previously used methods of studying leadership and management fashions in the scholarly scene.

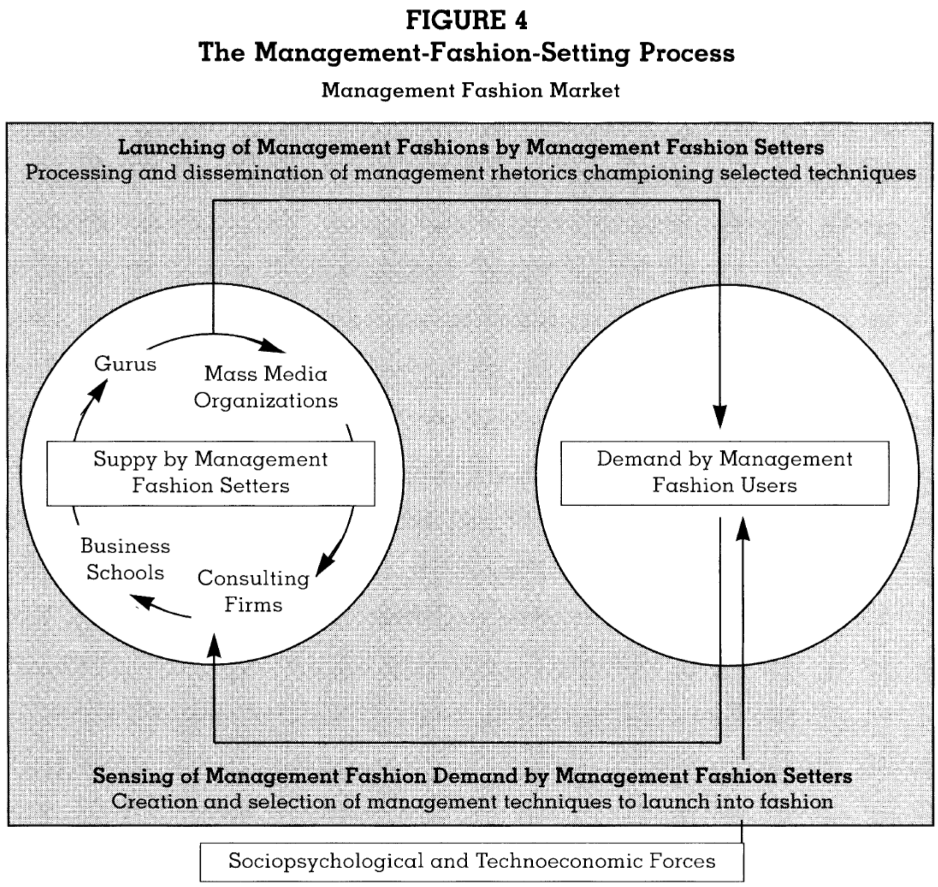

Figure 29: Abrahamson's Management-Fashion-Setting Process

Abrahamson (1996) recommends management scholars to increase their involvement in the entire management fashion setting process in order to not fall behind as a shaping force in the management fashion setting process; hereby scholars avoid losing the support of their stakeholders. For the time of his publication, Abrahamson saw a strong pull by the managers' demand for newer, improved and effective management techniques and a push by the fashion setters' supply of sufficiently novel management techniques to be perceived as an advancement over previous management techniques. Abrahamson sees the opportunity for management scholars to increase their participation in the circular management fashion setting process with several initiatives that change how they are perceived. They are perceived that they are not at the forefront of the progressive management fashion setting movement and hereby allow other actors of the supply side to create persuasion rhetorics and facilitate the diffusion of newly developed management techniques (Abrahamson, Management Fashion, 1996).

Guthey argues that an added and extended element of norms and expectations with an emphasis on different modes of rationality allows us to adapt this model to leadership studies (Guthey, Ferry, & Remke, work in progress). There appears to be a consensus between both Abrahamson and Guthey; that there is an element of social construction involved in the creation, emergence and institutionalization of fashions. Our study supports this notion and we further argue on the basis of this study that there appears to be isolated supply and demand circles present in both leadership and management studies. Our data shows no correlation between the three subsets, leading us to the conclusion that the supply and demand circles are not as clear or ingrained as we originally thought. Thus, supporting the idea that supply and demand circles can be individually constructed between two actors and not influenced by outside forces.

Arguably, it would be logical that Academia would be an omnipresent force that acted as the fashion setter for all other actors. However, the results of our study of Leadership fashions indicate that Academia (i.e. scholars) does not have the role of fashion setter in this process, because we are unable to see on the one hand a universally valid way of diffusion of leadership paradigms across the three observed subsets and on the other hand, the NMDS graphs have shown that the vocabulary used in Academia is clearly differentiated from the vocabulary of the other two subsets meaning that spill over of words and fashions from Academia to other subsets is unlikely to happen.

5.3.1 Obvious findings

The NMDS plots that we have produced have shown that the words used in Academia are characterised by two particularities. The first one is the strong degree of overlap of words used in the Academia subset over the observation time period. This means that the words do not change drastically from year to year and that they are in general very similar to each other. The second particularity is the fact that both for Leadership and Management (serving as our cross-checking mechanism) the word clusters for Academia were always visibly separated from the other subsets, meaning that the language used in Academia is usually not shared to a larger extent with the language used in either Business or Education. This is particularly interesting as we were expecting that Education and Academia are closer to each other as they are part of the same institutions despite having different focus areas.

The question that remains to be answered is why the language of Academia is so different from the other subsets and how does this impact the diffusion of leadership paradigms between the subsets.

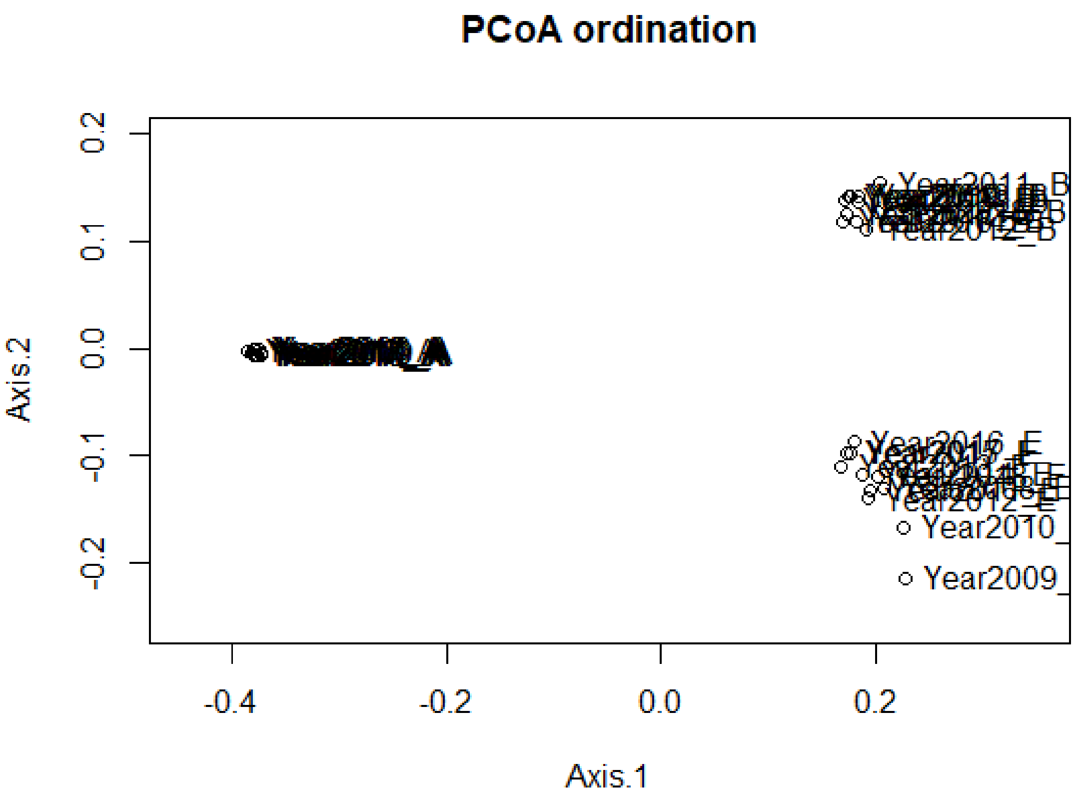

Figure 30: NMDS plot for all Leadership subsets

One way of thinking of the language uniformity within Academia and the distance that this creates from the other datasets, is the language criteria used in Academia to create professionalism and reliability within the academic community. Similar to the referencing standards that enable retracing the sources of any given paper, the language itself used in academic materials is also subject to similar norms. For one, in most academic instances English is used as the default language of communication. It is easy to see why English is chosen over any other language ranging from the reach of English to the presence of English in other international scenarios like politics, entertainment, social media and many more (Mauranen, 2010).

The language uniformity and specificity in Academia has also been mentioned by Abrahamson when he argues for a stronger intervention of management scholars in the management fashion setting process by stating that scholars should post a clearer message and refrain from relying too much on a “scholarly jargon” (Abrahamson, Management Fashion, 1996, p. 278). Murray (2013) further advances that Academia frames its contents with partly adverse outcomes like altering the meaning of statements or masking core messages of statements behind a veil of academic language and style (Murray, 2013). We see proof for Murray’s statement also in the outcome of our dataset, especially considering the Leadership NMDS plot shown in Figure 26 which shows a clear frame for the academic language. We see the presence of this frame via two particularities of our NMDS plot. Firstly, it shows the strong overlap of the vocabulary used in Academia, which is unmatched by neither Business nor Education, meaning that Academia puts special emphasis on the alignment of vocabulary and words used within the academic realm. Secondly, Academia is visually clearly apart from Business and Education limiting the spill-over of words across subsets and also the intent of Academia to set itself apart from the other subsets in terms of words and vocabulary. This in turn then makes it more difficult to retrace how language and words used diffuse across the subsets especially when the language within Academia is strongly contained.

Besides the framing of words and language in Academia, we also see a lot of literature on the market that intends at introducing newcomers to writing and articulating arguments in the academic domain. The existence of this literature alone provides a first indication that Academia sets itself apart from the remainders of spoken and written language by articulating criteria that make one’s spoken and written words belong to the academic frame. If the message doesn’t adhere to a defined form and style guideline, then it potentially will be disregarded in the academic domain. Swales and Feak (1994) – authors of such a recipe collection for academic writing aimed at non-native English Graduate students – advance the adopted style of a written document must be aligned with content of the message and the audience that it targets (Swales & Feak, 1994).

It is safe to assume that also some rules and standards on style and form apply to the Business and Education subsets, but in a less pronounced and safeguarded way as they are in Academia. For one, the existence of peer-reviewing before publication is only found in Academia and is unusual in any of the other two subsets. We see the weaker enforcement of standards and form requirements in Business and Education reflected in the NMDS of Figure 26; we observe that both Business and Education are characterised by considerably lower degrees of overlap compared to Academia meaning that the vocabulary and words used within them have higher degrees of freedom.

Another aspect to observe and analyse besides vocabulary and words used is the amount of words used in each subset. By looking at the total number of unique words for each dataset, we establish how large the vocabulary base for each dataset is. This allows us to determine the amount of unique words per observation; an important measure to show the difference in reach between the two datasets. For the Leadership dataset we gathered a total of 40.882 observations and 22.931 observations for the Management dataset. Looking at the amount of unique words per dataset, we see the opposite with 37.968 unique words in Leadership and 42.734 words in the Management dataset. To calculate the unique words per observation ratio, we divide the number of unique words by the amount of observations for each dataset. By doing that, we arrive at a ratio of 0,93 for Leadership and 1,86 for Management.

The unique number of words per observation shows us that there is a difference in the spread of the vocabulary present in each dataset. It also supports the idea that, in general, we are dealing with a limited vocabulary. This further supports the notion that Academia, being placed as isolated as it is on the NDMS plots, must have a very specific and limited vocabulary for the subset to have such a placement compared to the other two subsets.

5.3.2 Unexpected findings

A central element in understanding why the NMDS plot shown above looks how it does in Figure 26 and why the vocabulary in Academia is so different from the words used in Business and Education is the way in which each of these subsets operates and how they interlink to each other. Our data shows that leadership fashions develop in Academia and we are furthermore certain that leadership fashions also exist in Business and Education; our data although cannot provide proof for the existence of leadership fashions in Business and Education. Therefore, it is equally difficult to exactly retrace the modes of diffusion between the subsets when we can only reliably identify the existence of fashions in leadership techniques in one of our three subsets.

The root cause for the absence of these diffusion patterns is the difference of vocabulary used in the three subsets that we see in our data and shown in the NMDS plots with the physical distance of each subset from another. The difference originates according to Abrahamson (1996) in the fact that different actors are trying to act as fashions setters (in Abrahamson's case management fashion setters) and are competing for the attention of the demand side that is mostly composed of managers that want to be perceived as being on the brink of progress. As Abrahamson elaborated, the academic scholars (our Academia subset) are increasingly losing the fashion setting competition against other actors from the Business and Education subsets like consultants, gurus, specialised literature and the like.

Because the share of scholarly contribution to leadership fashion setting is decreasing and other actors are taking over this role, the key success criteria for the presumed advances in leadership fashions change. Instead of focussing on the effectiveness of new techniques to improve organisations and solve essential problems, the focus moves to the novelty of a technique as the key criterion. It is a point that Clark (2004) raised by claiming that most fashion setting actors are concerned about the noise that their advanced techniques produce rather than the implications that their use in an organisational setting bring (Clark, The Fashion of Management Fashion: A Surge Too Far?, 2004).

Furthermore, some actors engaged as fashion setters act at the same time as intermediaries between the scholarly rhetoric and the end-customers of these techniques – the managers demanding techniques that provide them with an efficient and state-of-the-art leadership methodology.

The diffusion and manifestation of a fashion has been defined in a process by Suddaby and Greenwood (2001); they argue that the process happens in four stages; legitimation, commodification, colonization, and due diligence and innovation. Each of these stages in turn employs different actors and stakeholders. We argue that in a process of four stages with different actors and stakeholders on each stage, the prospect of a continuous and clear vocabulary diminishes greatly.

This is supported by Scarbrough (2002) who found in his study of Knowledge Management (KM) the following: "The analysis of KM's development suggests that the factors that promote the diffusion of a new fashion may in turn limit its translation into practice" (Scarbrough, The role of intermediary groups in shaping management fashions, 2002). Scarbrough continues by explaining that intermediary groups (i.e. consultancies) have a tendency to adapt a given paradigm to their specific target audience. Meaning that a fashion would start from a fashion setter and then be 'translated' by consultancies or other intermediaries to adhere to a specific clientele. This again supports the notion of different vocabularies as a reasoning, making it difficult to track a specific fashion through all three subsets.

It would appear logical to us as researchers, that the starting point of a fashion would be academic research. Then the fashion would diffuse through either Business or Education and be institutionalized and manifested. However, we see no evidence of this particular evolvement in our study. This is supported, as aforementioned, by Abrahamson (1996) and again by Abrahamson and Eisenman (2001); here it is argued that scholars must prepare themselves for an everchanging market and be prepared as demand increases, so will supply. Abrahamson and Eisenman are pleading fellow scholars to understand that the market of management fashions will be flooded, and it is therefore important for scholars to maintain their stand as an authority. But our study shows that the authoritative role of academic researchers appears to be non-existent.

5.3.3 Ambiguous findings

As we have observed throughout the analysis, we can see that there appears to be fashions throughout the three subsets. Especially the cluster graph around the word *transformational* has been essential to identifying fashions throughout and across the three subsets. However, based on the aforementioned divergence in vocabulary and lack of clear diffusion, we cannot prove a fashion that transcends between Academia, Business and Education for the rest of our dataset nor can we prove with certainty that fashions do not exist at all. Our data set only provides concrete proof for the existence of leadership fashions in Academia. As we have previously seen, the linear and coherent development of leadership in Academia is shown both in the NMDS plot for Academia (Figure 10) as well as the Academia cluster graphs (Figure 16). The NMDS plots and cluster graphs for Business and Education do not provide conclusive proof for the existence of leadership fashions, as the random developments that we have found in Business and Education based on our data are portraying conflicting results and do not allow a conclusive interpretation. This consequently makes our findings for leadership fashions in Business and Education ambiguous, because we know that they exist, but we cannot proof their existence. For every argument in favour of the leadership fashions in Business or Education that we can make, there is at least one piece of counterevidence that annuls that argument.

By conducting this study in the manner in which we did, we allowed the data to speak for itself. This means that the clusters investigated were created by the data itself, thus eliminating as many types of biases as possible. This in turn provided us with clusters of words that do not necessarily appear logical for this particular subject. By doing this we investigated the raw amount of data without taking the amount of 'noise' (Clark, The Fashion of Management Fashion: A Surge Too Far?, 2004) that is undoubtedly present. We argue that for this specific study, the noise it necessary to achieve the correct picture of a potential diffusion. The lack of diffusion is therefore highly affected by the noise but nevertheless still relevant and true. In order to make the diffusion of fashions visible, we were observing the development of clusters around three identical words (*authentic*, *complex*, *transformational*) across Academia, Business and Education hoping to escape the noise created by the amount of data. Unfortunately, this observation resulted in three different patterns of diffusion thereby hindering us at drawing a conclusion on diffusion patterns for leadership fashions. Different data sources and a stronger adherence to manually picked clusters compared to the clusters that naturally develop from the data might increase the likelihood of finding reliable fashion diffusion patterns in future research.

Chapter 6: Conclusion

6.1 Concluding our study of leadership fashions and its diffusion

We are concluding our study with recapitulating its method and the results that we found along the way of the study. We finish by revisiting what it means in terms to the research questions that we posed at the beginning of our study.

For our analysis, we put emphasis on the capacity in which the data would talk for itself and document the patterns that became subsequently visible. This was with the aim of finding with the help of big data diffusion patterns of words and word usage to enhance the study of leadership and management fashions as well as finding proof for academic's role as leadership fashion setters. We started initially by creating NMDS plots that helped us understand the general composition of our data subsets and to place the vocabulary used in each subset in relation to the vocabulary used in the other subsets. To get this overview, we firstly created an aggregate NMDS plot for our leadership dataset that plotted Academia, Business and Education into the same ordination map and we found that each subset has a distinct set of words that is clearly different from any of the others. With the help of this NMDS plot we found that Academia exhibit the highest degree of word overlap meaning that it is the less diverse subset in terms of variation of words used from our three studied subsets. Education appears to be the subset exhibiting the lowest the degree of overlap and thereby should contain a more diverse set of words than for the ones observed for Academia and Business. In a second step, we drew individual NMDS plot for each subset that showed us how diverse the vocabulary and words used in each subset are. For Academia, our NMDS plot showed a linear relationship of the years indicating a linear and coherent development over the years that could mean that leadership fashions in Academia exist. The leadership Business NMDS plot offers a different if not fundamentally different picture from the Academia NMDS plot. It shows a considerably weaker linearity of the yearly points but still keeps it to a certain extent by grouping the years together. This shows us that the words and word usage within Business is not a restricted as in Academia but that it goes through more pronounced changes (jumps) in vocabulary. Lastly, we observed the NMDS plot for our leadership Education subset that provided us with the least clear-cut picture and indicates that the words and word usage within Education is typically not following any recognisable patterns which makes it more difficult to draw any conclusions from the output that we have seen for Education.

Following the plotting of the subsets and the observed years into NMDS plots, we were interested in seeing the clusters of words contained in our leadership dataset. To identify and determine clusters, we produced various heatmaps of our subsets containing a line for each word and a column for each year of our observation period from 2008 to 2018. The heatmaps facilitate the visual identification and determination of heatmaps and allowed us to make records of the clusters shown in each subset that were the basis for the next steps of our analysis to go more into depth with each cluster and the clusters within each subset. The sums of each word's explanation rate for each cluster delivers an aggregate explanation rate that we used to create linear graphs for all the clusters within the same subset offering us a comparative view of the clusters contained in a subset at once. Initially we just compared the clusters individually within each subset to each before we manually selected clusters containing the same key word that we traced across the three subsets of Academia, Business and Education.

The comparison of the clusters within the same subsets delivered similar results to what we have already observed in our NMDS plots. The leadership clusters in Academia exhibited the most linear developments over the observation period with none of the curves showing abrupt developments or other random outbursts. The Business clusters in leadership are the middle ground between Academia and Education exhibiting some volatility and some peaks and slumps of the curves without looking completely random or driven with outliers. Education exhibits very volatile graphs that seem to be not guided at all by linearity of any sort. Specifically, the year 2009 seems be the trigged for most of the maxima and minima of the curves; something that we haven't observed elsewhere. It is certain to say that Education gave us rather little insight into understanding leadership fashions and the way in which they diffuse. Here the clusters anchored around the three words authentic, complex and transformational were more helpful with recording the patterns of diffusion across subsets because we have seen how the clusters behave across Academia, Business and Education when some of the words remain constant across the clusters. Nevertheless, we could not deliver any conclusive and universally valid pattern of diffusion across all three as every word-cluster rendered a different order of transcendence. For transformational we have observed that Academia sets that fashion and that it then diffuses first to Business before it reaches Education. For complex it appears that for many years it diffused first to Education after it was established as a fashion by Academia and before it finally reaches Business. Lastly, complex provided no conclusive pattern at all with each subset being at least once on top of the other subsets and thereby not allowing us to draw any meaningful conclusion from it.

In order to verify if the fashion behaviour is unique to leadership, we gathered the same data for management by setting the same dataset delimitation criteria that we have used before for the leadership dataset. Our comparative study showed slightly different outcomes compared to our study of leadership fashions before. The main differentiators to leadership we found was the lower degree of overlap between the subsets resulting in a higher likelihood of word spill-over across the three subsets. Here again the Academia subset showed a strong overlap of its data points presenting the highest degree of word uniformity of all three subsets. Business and Education were more fluid than their counterparts in the leadership dataset. The most interesting differentiation between leadership and management that we found was the abundance of literature and academic research on each topic. Where the Google Ngram showed a clearly higher number of books on management compared to leadership books for the years 1900 to 2008, the number of academic articles between 2008 and 2018 shows the opposite trend. In 2008, the number of articles in management was still higher than the number of articles in leadership, but for 2009 and the years up to 2018 the trend inverses. The number of leadership articles clearly outnumber the number of articles in management. It is interesting to see that while the overall number of leadership articles climbs between 2008 and 2018, the number of articles in management declines for our observation period. This could mean that scholars are increasingly moving from researching management to researching leadership.

Relying on the methods that we have developed, our dataset shows different findings for each subset making it difficult to conclude uniformly across the full width of our dataset. Therefore, we offer a more differentiated approach to our findings. Our analysis shows a moderate fashion effect in academic research of leadership over our ten-year observation period, but at the same time it fails to provide conclusive evidence for the existence of fashion patterns within Business and Education. This in turn implies that our dataset cannot retrace the diffusion of fashion patterns across the three contexts and that it cannot validate in any capacity the findings of previous research that academics play a predominant role as fashion setters in management and leadership. At the same time, our diverging results across the three subsegments of our analysis (Academia, Business and Education) do not rule out the possible role of academic scholars as fashion setters or the existence of leadership and management fashions; they question the status quo of leadership and management fashion research and the ways in which these topics have been studied until now. We offer a different, comprehensive set of tools to investigate their existence and the diffusion patterns and invite scholars to familiarise themselves with these methods because it allows them to dig deeper into the management and leadership fashion domain going forward. We draw on interdisciplinary methods from natural sciences and statistics that augment our understanding and knowledge of these fashions and that elevate the leadership fashion discipline from an argument-based to a fact-based discussion.

We conclude that big data technologies can help make leadership and management research more relevant by drawing on more direct forms of data that is available in exponentially greater quantities and it makes this research less prone to shifts or fluctuations triggered by conflicting paradigms and discussions. Big data methods rather offer a solid foundation with results that are reproduceable and leave little room for individual argumentation.

Lastly, our study that relies on these methods further provides scholars with a more realistic assessment of their role and their influence over the diffusion of leadership and management fashions and techniques. Potentially other actors also play a considerable role in the leadership and management fashion setting process making it a more co-created exercise than previous leadership and management fashion research has accredited.

6.2 Limitations of the study

As with every study, also our study is unable to cover all potential scenarios and therefore exhibits limitations that everyone reading this study should be aware of to interpret the results in an accurate and reliable manner.

Firstly, the method we have chosen is limited by the share of data that is publicly available online on the Internet. This is especially limiting for the gathering of the Business and Education data subsets. It took us considerable time to determine selection criteria that create somehow relevance and comparability in our dataset. The method limited it to the data that is available on the websites of the respective companies that fulfilled our specified selection criteria. This raises obviously the question of how representative the information published on each company's website is and if there are better ways of acquiring the relevant data. We need to answer this question with yes because there are other ways of gathering more accurate data for this means, but at the cost of bias. In order to know what Business and Education actors are offering and demanding in leadership training and advising, it would necessarily to engage with the actors to receive another level of detail. That in turn would mean that it introduces bias to the data sample as it would be subjected to what information the actors want to share with us and be dependent on the way that we as the interviewers frame the questions. Therefore, we decided that despite the representativity concerns, we would limit ourselves to the amount of information that is publicly available as this puts all actors onto the same level; each actor has the possibility to publish as much information as they want on their websites leaving the bias with them. We want to emphasise that this limitation is especially true for the Business and Education subsets, as the Academia subset is different from the other subsets.

Secondly, the amount of datapoints that our delimitation criteria have triggered, create noise by the nature of their abundance. Despite our best attempts to let the dataset talk by itself, our selected method cannot fully guarantee that every meaningful datapoint has been considered and contributed to our results. Simply due to the sheer amount of datapoints that we gathered and the noise that a dataset of 160 million data points creates, we potentially have disregarded some datapoints that could have made a meaningful contribution to our study. We are aware of this limitation, but at the same time argue that due to the time and size constraints of our study, we could not have considered every data point individually despite the consequences this has.

Thirdly, we can argue that creating the Academia subset based on only one database of academic publications (in our case: Business Case Complete) might not be sufficient to draw a full and reflective picture of the proceedings of academic Leadership research. We limited ourselves to only one academic database because that single database managed to deliver over 16.000 abstracts of academic papers over our ten-year observation period, providing us already with a sufficiently rich subset sample for Academia. Already with only one academic database as the input for our study, we gathered a rich data sample allowing us to identify trends within Academia.

Fourthly, the initial groundwork to create the selection criteria for our data sample were littered with obstacles. It was rather difficult to install replicable selection criteria for the Business sample that would be realistic, unbiased and deliver an acceptable result. After multiple iterations, we decided that leadership development and executive search companies adhering to AESC would be the basis for our Business data sample as we see AESC as the institution that would verify if a company is working and advising in said domain. This again creates bias but this time with the AESC membership accreditation because not every company active in that domain might actually seek a membership with AESC. Despite being a source of bias, it is not bias that has been introduced by us as the researchers.

Fifthly, we are also encountering technical limitations that dictated how we could carry out this research. For one the availability and emergence of the Internet can be a limiting factor especially as our study goes as far back as 2008 where maybe not every academic paper was published online and not every company or business school had a relevant online presence via a dedicated website. This might limit the number of relevant matches with our selection criteria especially for the early years of our study. It is safe to say that for the more recent years this should not have been an issue. Another technical limitation is found with the Wayback Machine – our online repository of previous versions of websites – and more specifically with the intervals in which the Wayback Machine creates a snapshot of each website. The intervals in which a snapshot is taken is not regular but triggered when changes are made to websites by their owners. In other words, the Wayback Machine only saves a new snapshot of a website when the website has been updated. This consequently means that occasionally the snapshots for different years of the same website can be identical until the website is changed. If no updates have been made since the previous year for which we started a query, then the Wayback Machine will provide us with the snapshot that follows chronologically next, hereby skewing the result for the query of a specific year.

Lastly, by the nature of our study design, we focus more strongly on the supply side than on the demand side of Leadership techniques as the demand side is more individualistic and less publicly available. We accept this bias towards the supply side by acknowledging that our reliance on publicly available online data and note that we retain coherence by applying it to the three analysed subsets of our study.

Despite the limitations we encountered in our study, big data offers big promises improved insights in a variety of different research areas that have been so far mostly carried out with qualitative methods. Our study is to the best of our knowledge the first time that someone has applied big data technologies to this type of research and should serve as a blueprint for many future studies that have traditionally been based on qualitative research methods.

6.3 Recommendations for further research (actionable insights)

All of the above-mentioned can of course be mitigated or avoided in future research that aims at analysing our study domain in a greater detail. We further offer the following insights that extends our foundational study.

A first point in which further research can be improved is abandoning the limitation imposed by the Internet, meaning that further research could investigate the materials provided by consultancies for the Business subset and program curriculums from business schools for the Education subset. This especially avoids the limitations that we encountered for the data aggregation of our Business and Education subsets. In order to not create unnecessary bias, we would recommend focusing on materials provided by the consultancies or the business schools instead of using interviews as a data source. Engaging in interviews would introduce bias created by the interviewer as well as the interviewee, whereas the simple analysis of provided materials is in terms of data gathering and evaluation comparable to our methodology.

Another way of trespassing our limitations is choosing more than one academic database for the construction of the Academia subset. As the data gathering strategy for Academia differs from the ones employed with Business and Education, further research could very easily extend the scope beyond Business Source Complete as a source and add other academic database for the Academia subset. It should nevertheless be noted that this increases the range of the Academia subset, but not necessarily its quality or meaning.

Lastly, in order to avoid the limitations that we ran into with the Wayback Machine, we would recommend changing the research design from a backward, historical web-scraping search to something that resembles a longitudinal study and records the words used in a leadership context in the subsets for the coming ten years. Although a forward-looking study requires a much longer data gathering phase, it avoids that elements or words get lost because they have not been properly recorded or saved. The choice for a historical or forward-looking data gathering depends if speed of the research or completeness of the data is prioritised.

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rt=1900&year_end=2015&corpus=15&smoothing=1&share=&direct_url=t1%3B%2Cmanagement%3B%2Cc0%3B.t1%3B%2Cleadership%3B%2Cc0#t1%3B%2Cmanagement%3B%2Cc0%3B.t1%3B%2Cleadership%3B%2Cc0

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Appendix A – Code scraping text from websites

```
Option Explicit
Private Declare Sub keybd_event Lib "user32" (ByVal bVk As Byte, ByVal _
bScan As Byte, ByVal dwFlags As Long, ByVal dwExtraInfo As Long)
Private Const VK_SNAPSHOT = &H2C
Global Const SW_MAXIMIZE = 3
Global Const SW_SHOWNORMAL = 1
Global Const SW_SHOWMINIMIZED = 2
Sub PrintScreen()

Dim IE As Object
Dim elems As Object
Dim e As Variant
Dim objCollection As Object
Dim docComplete As Boolean
Dim hc, starthref, theurl, orow, web, r1, name, geo, i, j, year, r2, k, nu, time
Dim webtext As Variant


For i = 0 To 20765
   r1 = i
   web = Worksheets("sublink").Range("C" & r1).Value
   name = Worksheets("sublink").Range("A" & r1).Value
   geo = Worksheets("sublink").Range("b" & r1).Value
   year = Worksheets("sublink").Range("f" & r1).Value

   Set IE = CreateObject("internetExplorer.Application")
```

```
With IE
 .navigate "http://web.archive.org" & web
 nu = Now
 time = nu + TimeValue("00.00.10")
 Do: DoEvents: Loop Until .readystate = 4 And Not .busy Or time < Now
 Do: DoEvents: Loop Until .document.readystate = "complete" Or time < Now

 If time > Now Then

 hc = .document.body.innertext

 If InStr(LCase(hc), LCase("leader")) <> 0 Then
 webtext = Split(hc, vbCrLf)
 For k = 0 To UBound(webtext)
    'MsgBox (webtext(k))
    If InStr(LCase(webtext(k)), LCase("leader")) <> 0 And InStr(webtext(k), "<") = 0 Then
    orow = Sheets("Text").Cells(Rows.Count, 1).End(xlUp).Offset(1).Row
       Worksheets("Text").Range("A" & orow) = name
       Worksheets("Text").Range("b" & orow) = geo
       Worksheets("Text").Range("c" & orow) = theurl
       Worksheets("Text").Range("d" & orow) = year
       Worksheets("Text").Range("e" & orow) = web
       Worksheets("Text").Range("f" & orow) = webtext(k)
       ActiveWorkbook.Save
    End If

 Next
 ActiveWorkbook.Save
 End If
```

```
    IE.Quit
    Set hc = Nothing
    Else
    IE.Quit
    Worksheets("sublink").Range("h" & r1) = "slow"
    ActiveWorkbook.Save
    End If
    End With


Next
```

Appendix B – Code scraping URLs from websites

```
Option Explicit

Private Declare Sub keybd_event Lib "user32" (ByVal bVk As Byte, ByVal _

bScan As Byte, ByVal dwFlags As Long, ByVal dwExtraInfo As Long)

Private Const VK_SNAPSHOT = &H2C

Global Const SW_MAXIMIZE = 3

Global Const SW_SHOWNORMAL = 1

Global Const SW_SHOWMINIMIZED = 2

Sub PrintScreen()


Dim IE As Object

Dim elems As Object

Dim e As Variant

Dim objCollection As Object

Dim docComplete As Boolean

Dim hc, starthref, theurl, orow, web, r1, name, geo, i, j, year, r2, k, nu, time

Dim webtext As Variant



For i = 0 To 20765


   orow = Sheets("sublink").Cells(Rows.Count, 1).End(xlUp).Offset(1).Row



   Do

   DoEvents
```

```
    starthref = InStr(hc, "href")
    If starthref > 0 Then



        theurl = Mid(hc, starthref + 6, Len(hc))
        hc = Mid(hc, starthref + 6, Len(hc))
        theurl = Mid(theurl, 1, InStr(theurl, Chr(34)) - 1)
        If InStr(theurl, web) <> 0 Then
            orow = orow + 1
            Worksheets("sublink").Range("A" & orow) = name
            Worksheets("sublink").Range("b" & orow) = geo
            Worksheets("sublink").Range("c" & orow) = theurl
            Worksheets("sublink").Range("d" & orow) = year
            Worksheets("sublink").Range("e" & orow) = web
        End If

    End If
    Loop Until starthref = 0

    IE.Quit
    Set IE = Nothing

    End With
Next

Next



keybd_event VK_SNAPSHOT, 1, 0, 0
```

```
Dim MW As Object
Set MW = CreateObject("Word.Application")
MW.Visible = True
MW.Activate
MW.Documents.Add
MW.WindowState = wdWindowStateMaximize
MW.Selection.Paste
keybd_event VK_SNAPSHOT, 1, 0, 0
Activeword.Paste

End Sub
```

Appendix C – Code determining unique words

```
Sub WordFrequency()
    Const maxwords = 500000       'Maximum unique words allowed
    Dim SingleWord As String      'Raw word pulled from doc
    Dim Words(maxwords) As String  'Array to hold unique words
    Dim Freq(maxwords) As Long  'Frequency counter for unique words
    Dim WordNum As Long        'Number of unique words
    Dim ByFreq As Boolean        'Flag for sorting order
    Dim ttlwds As Long          'Total words in the document
    Dim Excludes As String       'Words to be excluded
    Dim Found As Boolean        'Temporary flag
    Dim j, k, l, Temp As Long   'Temporary variables
    Dim ans As String           'How user wants to sort results
    Dim tword As String          '

    ' Set up excluded words
    Excludes =
"[the][a][of][is][to][for][by][be][and][are][in][that][an][on][from][this][abstract][doi][we][as][with][j
][their][y][author][copyright][these][was][which][has][more][how][have][were][or][can][it][our][at
][also][not][when][two][they][its][both][but][through][than][been][about][may][such][well][one][th
ree][e][who][s][what][there][some]"

    ' Find out how to sort
    ByFreq = True
    ans = InputBox("Sort by WORD or by FREQ?", "Sort order", "WORD")
    If ans = "" Then End
    If UCase(ans) = "WORD" Then
        ByFreq = False
    End If

    Selection.HomeKey Unit:=wdStory
```

```
System.Cursor = wdCursorWait
WordNum = 0
ttlwds = ActiveDocument.Words.Count

' Control the repeat
For Each aword In ActiveDocument.Words
  SingleWord = Trim(LCase(aword))
  'Out of range?
  If SingleWord < "a" Or SingleWord > "z" Then
    SingleWord = ""
  End If
  'On exclude list?
  If InStr(Excludes, "[" & SingleWord & "]") Then
    SingleWord = ""
  End If
  If Len(SingleWord) > 0 Then
    Found = False
    For j = 1 To WordNum
      If Words(j) = SingleWord Then
        Freq(j) = Freq(j) + 1
        Found = True
        Exit For
      End If
    Next j
    If Not Found Then
      WordNum = WordNum + 1
      Words(WordNum) = SingleWord
      Freq(WordNum) = 1
    End If
```

```
        If WordNum > maxwords - 1 Then
            j = MsgBox("Too many words.", vbOKOnly)
            Exit For
        End If
    End If
    ttlwds = ttlwds - 1
    'StatusBar = "Remaining: " & ttlwds & ", Unique: " & WordNum
Next aword

' Now sort it into word order
For j = 1 To WordNum - 1
    k = j
    For l = j + 1 To WordNum
        If (Not ByFreq And Words(l) < Words(k)) _
          Or (ByFreq And Freq(l) > Freq(k)) Then k = l
    Next l
    If k <> j Then
        tword = Words(j)
        Words(j) = Words(k)
        Words(k) = tword
        Temp = Freq(j)
        Freq(j) = Freq(k)
        Freq(k) = Temp
    End If
    'StatusBar = "Sorting: " & WordNum - j
Next j
' Now write out the results
tmpName = ActiveDocument.AttachedTemplate.FullName
Documents.Add Template:=tmpName, NewTemplate:=False
```

```
    Selection.ParagraphFormat.TabStops.ClearAll
    With Selection
        For j = 1 To WordNum
            .TypeText Text:=Trim(Str(Freq(j))) _
              & vbTab & Words(j) & vbCrLf
        Next j
    End With
    System.Cursor = wdCursorNormal
    j = MsgBox("There were " & Trim(Str(WordNum)) & _
      " different words ", vbOKOnly, "Finished")
End Sub
```

Appendix D – Commands in R

```
-----------------------------------------------------------------------------------------
# Combine files in R
dat <- read.table("D:/Allwords/EducationAllWords 1.1.txt",sep="\t")
dat2 <- read.table("D:/Allwords/EducationAllWords 1.2.txt",sep="\t")
a <- cbind(dat, dat2)
write.table(a, file="D:/Allwords/Education_full_data1.1_1.2.txt", sep="\t")
dat3 <- read.table("D:/Allwords/EducationAllWords 2.1.txt",sep="\t")
dat4 <- read.table("D:/Allwords/EducationAllWords 2.2.txt",sep="\t")
b <- cbind(dat3, dat4)
write.table(b, file="D:/Allwords/Education_full_data2.1_2.2.txt", sep="\t")
dat5 <- read.table("D:/Allwords/EducationAllWords 3.1.txt",sep="\t")
dat6 <- read.table("D:/Allwords/EducationAllWords 3.2.txt",sep="\t")
b <- cbind(dat5, dat6)
write.table(b, file="D:/Allwords/Education_full_data3.1_3.2.txt", sep="\t")

dat7 <- read.table("D:/Allwords/Education_full_data1.1_1.2.txt",sep="\t")
dat8 <- read.table("D:/Allwords/Education_full_data2.1_2.2.txt",sep="\t")
c <- rbind(dat7, dat8)
write.table(c, file="D:/Allwords/Education_full_data1.txt", sep="\t")

dat9 <- read.table("D:/Allwords/Education_full_data1.txt",sep="\t")
dat10 <- read.table("D:/Allwords/Education_full_data3.1_3.2.txt",sep="\t")
c <- rbind(dat9, dat10)
write.table(c, file="D:/Allwords/Education_full_data.txt", sep="\t")

--------------------------------------------------------------------------
# Normalization of the data
library(dplyr)
data <- read.table("D:/Management/BusinessManText.txt", sep="\t", header=T)
#replace NAs
data[is.na(data)] <- 0
dt <- aggregate(. ~Year, data=data, sum, na.rm=TRUE)
write.table(dt, file="D:/Management/Business_full_data_collapsed.txt", sep="\t")
word <- read.table("D:/Management/Business_full_data_collapsed.txt", sep="\t")
#I transposed the table in Excel
data <-
read.table("D:/Management/Business_full_data_collapsed_transposed_percent.txt",
row.names=1, sep="\t", header=T)

_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _
_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _
library("dplyr")
library("vegan")
```

```
library("ape")
library("MASS")

#make the PcoA plot
dist <- vegdist(t(data))
distPcoA <- pcoa(dist)
distPcoA$values
biplot(distPcoA)

# Heatmaps
library(pheatmap)
pheatmap((log(t(data+1))), cluster_col=FALSE, cellwidth = 15, cellheight = 12, fontsize = 8,
color = colorRampPalette(c("blue", "white", "red"))(50), filename = "
D:/Allwords/Business_total_heatmap.pdf")
library(cluster)
fit <- kmeans(data, 8)
clusplot(data, fit$cluster, color=TRUE, shade=TRUE, labels=2, lines=0)

#If you want to write out the components into an excel file
a <- fit$cluster
write.table(a, file=" D:/Allwords/Business_cluster_table.txt", sep="\t")
```