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Critical Effect: Contextualizing Performance in Business Schools using the h-Index

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Abstract

Faculty performance assessments increasingly use the h-index. Designed to account for publication quantity and effect, the h-index informs organizational discussions and internal narratives. However, its use in business schools is problematic for two reasons. First, tension exists between the positivist approach of management and the reflexive approach of critical management studies. Second, the use of the h-index is hegemonic, privileging one group and construct over another. Given the power asymmetry between senior and junior faculty, discussions around one's h-index could be unavoidable. Using Google Scholar, this study compared the h-index values of those in critical management studies with those in management. Examining these data descriptively revealed that the h-index of those in critical research were greater than those in management at the assistant, associate, and full professor levels. Incorporating these findings, even if skeptical of positivism, is constructive for the advancement and continuation of critical business research.

Keywords

Professional identity; epistemology; narrative; work assessment

Introduction

Focused discussions pivot around reference points (Bonaiuto & Fasulo, 1997; Searle, 1997; Shotter, 1995). In academia discussions of performance frequently center on faculty publications (Burbules, 2020; Haven, Bouter, Smulders & Tijdink, 2019; Heng, Hamid & Khan, 2020; Yeo, Renandya & Tangkiengsirisin, 2021). Since it accounts for both an author's publication volume (i.e., number of publications) and impact (i.e., number of citations), the *h*-index is increasingly used as a measure of scholarly performance (Kelly & Jennions, 2006; Mingers, 2009; Szpalski, Gunzburg & Aebi, 2014). For those engaged in organizational discussions and internal narratives around academic performance, the increased prominence of the *h*-index makes it relevant for added scrutiny as to how it has been applied. The *h*-index has been applied to assess the performance of faculty

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from a variety of academic disciplines, including engineering (Loizides & Koutsakis, 2017; Noble & Kecojevic, 2015; Rautaray, Swain & Swain, 2013; Tahira, Abdullah, Alias & Bakri, 2018), political science (Andersen & Nielsen, 2018; Bernauer & Gilardi, 2010), psychology (Barner, Holosko, Thyer & King, 2015; García-Pérez, 2010; Haslam, Stratemeyer & Vargas, 2017), and sociology (Dabós, Gantman & Fernández Rodríguez, 2019; Jacobs, 2016). And while the *h*-index has been applied to various aspects of business faculty assessment (Coleman, Bolumole & Frankel, 2012; Courtault, Hayek, Rimbaux & Zhu, 2010; Hwang, Arbaugh, Bento, Asarta, & Fornaciari, 2019; Valenzuela-Fernández, Merigó, Nicolas & Kleinaltenkamp, 2020), it has yet to be used to compare the relative performance of those faculty reportedly engaged in critical management studies (CMS) to those of management (MGT). Placing this comparison in context benefits from presenting a little background on the *h*-index.

To "quantify the cumulative impact and relevance of an individual's scientific research output," Hirsch (2005) proposed the *h*-index "as a particularly simple and useful" measurement of performance (p. 16569). It is useful to note that Hirsch, at the time of its inception, identified critical aspects associated with the use of the *h*-index, indicating, "a single number can never give more than a rough approximation to an individual's multifaceted profile… there will be differences in typical *h* values in different fields," and although "a high *h* is a reliable indicator of high accomplishment, the converse is not necessarily always true" (p. 16571). In other words, Hirsch admitted the *h*-index should not be used in isolation, it varies across academic disciplines, and a low *h*-index does not necessarily suggest an academic has not produced research of adequate quantity and impact. As previously mentioned, the *h*-index has gained wide usage within academia. Epiphenomenally to the ubiquity of the *h*-index is ambivalence surrounding its use. Jokstad (2016) acknowledged that while "the *h*-index along with other analogous author-level metrics indices is here to stay" there are "multiple reasons why we need to be skeptical to these artificial numbers" (p. 3). Even more critically, Gruber (2014) compared the pursuit of increasing one's *h*-index as a form of "academic sell-out" similar to "music bands that change their musical direction and give up their values to pursue commercial success" (p. 166). The lack of previous research exploring the *h*-index from a CMS perspective suggests that the empirical research presented here is timely and relevant. The critiques of the *h*-index suggest that a CMS perspective is useful for one's internal narratives and external discussions related to academic performance associated with publication. As such, it is useful to sketch contours related to CMS.

What is CMS? For those engaged in CMS it would be too reductionist to define its research, theory, and praxis as being described as any one thing. Taskin and Wilmott (2008) explained, "the diversity of CMS implies that it is a mistake to attribute too much commonality to its constituent elements and associated demands" (p. 31). And while there is legitimacy to the reticence of delimiting CMS too narrowly or formally, it is pragmatically useful to provide some contours as its most prominent features and ambitions. Phillips (2006) described CMS as being "in its adolescence" and that as such it is "struggling to form an independent identity and to understand how it can make an impact on the world" (p. 30). Fournier and Grey (2000) provided some delimitation to CMS when they explained that "although the pluralism of CMS…suggest that there is no ultimate way of tracing boundaries between critical and non-critical work… we suggest that the boundaries are drawn around issues related to performativity, denaturalization and reflexivity" (p. 17). CMS explores and critiques *power*, which can be considered an essential component of knowledge (Foucault, 1980; Lyotard, 1984). While distinct, CMS shares some conceptual ground with postmodernism. As Alvesson and Deetz (2000) positioned CMS, "both critical theory and postmodernism are oriented, in albeit different ways, to questioning established social orders, dominating practices, ideologies, discourses, and institutions" (p. 1). The crux of this dilemma is the gap between scientific and narrative knowledge. Lyotard explained how this gap was part of the "postmodern condition" by noting, "it is therefore impossible to judge the existence or validity of narrative knowledge based on scientific knowledge and vice versa: the relevant criteria are different. All we can do is gaze in wonderment at the diversity of discursive species" (p. 26). This research attempts to place these two forms of knowledge (i.e., scientific and narrative) in the closest proximity so our collective *gaze* can make use of and critique the findings as an input for discussions around academic performance. To accomplish this, it is essential to introduce the research question and approach.

This research should be of use to those engaged in CMS or MGT research and could be of interest to those engaged in postmodern organization theory. As Boncori, Bizjak, and Sicca (2020) explained, "professional expectations and practices in the Higher Education context have been evolving towards a neoliberal model of performance management" (p. 52). Such norms can be propagated through work assignments and assessment reviews. McDonald (2016) described the enculturation process of academia as a "'rite of passage' set by academic elite, where quick and proficient acquisition of institutionally-set standards was expected and required" (p. 1). Since the *h*-index is a potential measure of performance within academia it is worthy of consideration in this context. Making use of the *h*-index in such a way is particularly consequential as work can take on performative aspects (Jackson, 2011, 2022) and the adoption of the normative values and priorities of an institution holds the latent potential to influence both the formation of one's notion of self (Ehrensal, 2008; Tapani, 2009) and how that construction gets reflected back to an organization through formal documents like a self-assessment as part of a performance review or one's resume (Trester, 2016). From a critical perspective, the essential question is whether such a focus on the *h*-index as a measure of performance primarily serves "the goal to help management extract more productivity out of works" or allows for "more emancipatory ends" for the workers (Jaros, 2012, p. 56).

Observations for MGT and CMS faculty were obtained from Google Scholar on 8 August 2021. Each observation contained an h-index value and some of the observations also contained faculty rank information. These data were analyzed descriptively using a variety of analytic techniques. A comparative analysis of the scale between MGT and CMS was accomplished using a Venn diagram, whereas a comparative analysis of the dispersion within the two groups was accomplished with a boxplot. The relationship between the number of citations and h-index values was accomplished using scatter plots. To enhance the granularity of analysis, intervals of h-index values were created using percentages with the uncertainty assessed in the aggregate and at each faculty-rank level using Goodman and Kruskal's lambda (GKL), which measures the proportional reduction in error in cross-tabulation data. Since these are population data, and not samples, inferential statistical analysis and hypothesis testing were not conducted.

The *h*-index holds the potential to become a focal point for one's internal narratives and external discussions. Power asymmetry between senior and junior faculty could make discussions around one's *h*-index unavoidable. This study compares the *h*-index values between CMS and MGT at three faculty levels (i.e., assistant, associate, and full professor). The results of this analysis should provide those engaged in performance discussions within business schools a point of reference for these discussions. To accomplish this in a meaningful way, it is beneficial to place this analysis in context. This is accomplished by abstracting fragments of previous discourses related to the topic. These fragments cover a brief history of the *h*-index, its application in academia, an overview of CMS, and an exploration of epistemological antagonisms between CMS and MGT. After that review, the methodology and results are presented followed by a conclusion that covers the limitations of this study, possible extensions, and key points. It is now possible to engage more fully in the fragments of previous discourses.

Fragments of Previous Discourses

A survey of literature provides one with fragments of previous discourses. The intent is to provide one with an understanding of published research that is considered to be most meaningfully related to the current project (Baker, 2000; Torraco, 2016). However skillfully such a task is done, it literally requires taking material from one context and placing it into another. Any such recontextualization is consequential. Works by Derrida (1978, 1988, 1997, 2000) contain critiques of the enterprises of writing and context and are particularly useful in understanding how the original context of a work is broken upon citation. In response to recontextualization, Derrida (2000) explained, that "context is never absolutely determinable" (p. 3), and that any sign can be "put between quotation marks; in so doing it can break with every given context, engendering an infinity of new contexts in a manner which is absolutely illimitable" (p. 12). This section pivots around an integration of four discourse fragments: a) *h*-index history, b) applications of *h*-index in business, c) background into CMS, and d) antagonisms between CMS and business in terms of epistemology. Engaging with these discourses provides a useful setting for this research. Given the centrality of the *h*-index as the element of analysis, its history is presented first.

The *h*-index is a relatively new way to assess academic publication performance, being introduced by Hirsh in 2005. In that initial article, Hirsch (2005) proposed the *h*-index to assess both publication volume and impact in a single measurement but noted too that the use of *h*-index should not be used in isolation, that it varies across academic disciplines, and that one should not conclude that a low *h*-index is suggestive of poor academic publication performance. Early research related to the *h*-index found that there was a strong correlation with raw citation counts (Cronin & Meho, 2006), that it was resilient to missing articles and to missing citations (Rousseau, 2007), but that it didn't necessarily perform better than alternative methods (Kelly & Jennions, 2006). From a critical perspective, it is important to interrogate this *not better than*. Whereas equally informative alternatives to the *h*-index exist, one should not infer that there is something better. Critiques of the *h*-index have focused on its reductionist construction (Jokstad, 2016) and the potentially counterproductive behaviors it incentivizes (Gruber, 2014).

In response to the evolution in one's career and the corresponding effect this would likely have on one's *h*-index, Egghe (2007) suggested the *h*-index could be improved by making it a dynamic measurement through the incorporation of time. Such a modification is useful as one might reasonably expect faculty at different ranks to have different *h*-index values. Whereas there is certainly room to critique the *h*-index, Vanclay (2007) found that it was robust and could be used to assess both individual publication performance and academic journals. As such, it is useful for assessing previous performance. However, if promotion considerations include not only past performance but also expectations for future performance, such a retrospective metric answers only a part of the concern. Hirsch (2007) found that not only was the *h*-index useful for assessing past performance, but it is also predicted future achievement. As indicated in the introduction, the *h*-index has been applied in a variety of different academic contexts. For this study, its application in business is most relevant for further exploration.

Since its creation in 2005, the *h*-index has been applied to a variety of academic areas. Applications of the *h*-index to business domains are particularly relevant for this study. The *h*-index has been applied to assess the quality of business journals (Harzing & van der Wal, 2009; Mingers, Macri & Petrovici, 2012; Mingers & Yang, 2017; Valenzuela-Fernandez, Merigó, Lichtenthal & Nicolas, 2019) and business patents (Chang, Zhou, Zhang & Yuan, 2015; Guan & Gao, 2009; Magerman, Looy & Debackere, 2015; Zhang, Yuan, Chang & Ken, 2012). At the discipline level, the *h*-index has already been applied to the business fields of accounting (Adler, 2012; Schreiber, 2009), entrepreneurship (Ramírez, Cañizares & García, 2017; Terán-Yépez, Jiménez-Castillo & Sánchez-Pérez, 2021), marketing (Coombes & Nicholson, 2013; Martínez-López, Merigó, Valenzuela-Fernández & Nicolás, 2018), and MGT (Hwang et al., 2019; Mingers, 2009; Sahoo, Singh, Mishra & Sankaran, 2017). Orhan (2020) critiqued the underlying dynamics in the following terms:

> Scholarly impact is one of the most important life goals of every researcher… Adopting objective measures allows researchers and administrators to set standards; correctly assess the value of research contributions; and eliminate unfair treatments in recruitment, selection, promotions remuneration, and allocation of rewards… Incentives that fetishize the use of rankings heavily criticized in the literatures. Business schools are not short of journal lists and rankings… The meaning of prestige can be interpreted differently in different settings, as there are contextual boundaries, social contingencies, and local constraints. (pp. 304–305)

Whereas the *h*-index has been applied to compare the research between economics and management departments (Courtault, Hayek, Rimbaux & Zhu, 2010), as well as critique consequences of its use (Davison & Bjørn, 2019), research is lacking related to the use of the *h*-index as a basis for comparing faculty engaged in CMS and MGT research. With a better understanding of how traditional business schools have used the *h*-index, it is useful to turn now first to an overview of CMS and then to an examination of some of the antagonisms between CMS and MGT in terms of epistemology. Taken together, these threads of discourse help explain why there is a lack of research on how the *h*-index relates to CMS.

As indicated in the introduction, CMS is not *one* thing, but rather a collection of various critical stances taken regarding MGT. And while there might not be a universal definition of CMS, there are common themes that exist. Given the focus of CMS on narratives more direct quotes are used here to represent more fully the ongoing discourses. Dianati and Banfield (2020) explained that within CMS, "the key identifying features of the 'critical approach' are its epistemological commitment to social criticality and its pedagogical intent to foster student critical consciousness" (p. 341). When this is done within CMS, it is often accomplished through an assessment of narratives and discourses. According to Sułkowski (2019), CMS "took the form of institutionalized discourse" in the 1990s, with a focus on "treating management science as a persuasive discourse stemming from the assumption of capitalism, aiming to maintain the status quo based on dominance and exploitation" (p. 304). At its core the point of analysis is MGT, and the ways MGT subjugates workers. For Foster and Wiebe (2010), "CMS is concerned with the role of management and how management practices can and do lead to relationships of inequality and domination" (p. 271). The differences between CMS and MGT are not only a matter of the focus of inquiry, as the techniques used differ as well. Leebaw (2019) explained, "CMS researchers study management and workplaces using principles of defamiliarization, dissensus, and antiperformativity. Rather than taking existing structures as a given, they study how cultures and ways of doing work came to be within organizations" (p. 111). Through these critiques, CMS has been able to establish a role in ongoing MGT research and teaching. Alvesson, Bridgman and Willmott (2009) stated that "CMS has come to occupy and institutionalize a niche for teaching and research within business schools. Despite these achievements, however, its presence remains marginal and precarious" (p. 21). Understanding how the *h*-index of CMS scholars compares to those of MGT holds potential for strengthening the position of CMS. Examining the epistemological antagonisms between CMS and MGT could help in understanding why this comparison has been so long in coming.

Epistemologically, there is at least one significant point of divergence between CMS and MGT. Positivism resides at the core of traditional research but is largely eschewed in CMS. In critiquing the positivist foundations of research, Scherer (2009) noted that "the positivist model of explanation is always implicitly in the service of a specific interest – the interest in preserving the status quo by making the world technically controllable" (p. 38). Such a focus is placed squarely on MGT since one of its primary elements is control (Andrade & Ziegner, 2021; Shoubo Xu & Li Da Xu, 2011). In addition to control, notions of efficiency and objectivity are notionally aligned with MGT as it is traditionally conceived. Duberley and Johnson (2009) explained that CMS is "united by their rejection of any claim that management theory and practice are morally founded upon a technical imperative, to improve efficiency, justified and enabled by analyses of how things really are…CMS tends to be united by profound skepticism regarding the possibility of an objective and disinterested foundation for any knowledge" (p. 345). Rather than a positivist construction, CMS often makes use of a research methodology which is reflexive. Spicer, Alvesson and Kärreman (2009) asserted that CMS is *reflexive*, in that it "should challenge the implicit assumption around positivism that is often taken for granted" (p. 540). While there is value in the reflexive research enacted within CMS, it is possible and potentially beneficial to integrate positivist research into the narratives and discussions which are critically engaged with MGT.

These fragments of previous discourses focused on a brief history of the *h*-index, its applications in business schools, background in CMS, and the epistemological antagonisms between CMS and management. In summary, Hirsch (2005) proposed the *h*-index to quantify the number and impact of one's academic research. Since its inception, the *h*-index has been applied in business schools as part of faculty assessments. Identifying and critiquing such a metric is consistent with the broader CMS stance against things that privilege MGT over workers. Collectively, these snippets provide some context for this research. As indicated, CMS questions the hegemony of positivist constructions of knowledge. Such a position holds implications for methodology. The following section contains some notes on the methodological perspective used, which while positivism holds potential for constructivist interpretations of the results as part of one's internal narratives and external discussions.

Notes on a Methodological Perspective

Skepticism towards positivism and empiricism, and by extension quantitative analysis, has a longstanding tradition (Baldus, 1990; Hempel, 1954; Popper, 1959; Torgerson, 1986; Turner, 1986). Such suspicion resides within CMS. Alvesson and Deetz (2000) explained, “facts and data are produced and make sense only in the context of a particular framework that allows and guides us to see certain things and neglect others” (p. 63). Conducting CMS research might require operating within the tensions which exist between conflicting perspectives and priorities. Styhre (2009), noted that for those engaged in CMS “to be a researcher in a business school is to be *in-between*: in-between disciplines…in-between knowledge production and the field of application, in-between the academic researchers’ and the practitioners’ concerns and interests” (p. 30). Operating in this in-between space does not require that one reject empiricism, but rather than one admit to the dynamics of power that reside behind its use. Alvesson and Deetz concluded, “knowledge claimed in…institutions of science…is politically loaded…Issues of power are involved at each point…Critical research tries to engage in the power dynamics of truth in organizations without setting itself up as the final arbitrator of truth claims” (p. 47). The desire for CMS scholars to increase their interaction with those involved in more mainstream research is shared by Sage, Dainty and Brookes (2014). While the analysis produced here was created in the positivist/empiricist tradition, it is contextualized by CMS perspectives, with the intent that the results inform the narratives and discussions surrounding academic performance related to publications. The data were obtained from Google Scholar on 8 August 2021. A few words related to the source are in order before describing the data collection approach.

Google Scholar is a source for *h*-index values (Dabós, Gantman & Fernández Rodríguez, 2019; Delgado & Repiso, 2013; García-Pérez, 2010; Mester, 2017; Thyer, Smith, Osteen & Carter, 2019). As with any data source, especially when examined from a critical perspective, the benefit is derived through an interrogation of the relative strengths, weaknesses, and accuracy of the data. One advantage associated with using Google Scholar is that it indexes articles that are produced in languages other than English (Dabós, Gantman & Fernández Rodríguez). Another benefit is that Google Scholar is a “well-known multidisciplinary” platform (García-Pérez). Lastly, Google Scholar is significantly larger than either Scopus or Web of Science (WOS) (Delgado & Repiso). Consequently, using Google Scholar as the source of information provides a more inclusive and accessible point of comparison.

As a potential negative, Dabós, Gantman and Fernández Rodríguez (2019) indicated that Google Scholar might occasionally misattribute documents to authors or index documents that are not published articles and García-Pérez (2010) indicated that the citation counts were seriously inflated. While important, these negatives are not considered significant barriers for this study. First, the attribution errors identified were found to occur occasionally. Second, given the nature of the comparative analysis, the attribution error would be as likely to occur in one group as the other. Lastly, since this analysis examines the *h*-index values rather than the raw citation counts, any inflation associated with the citation counts will be muted by the conversion to *h*-index values. The view that the limitations associated with Google Scholar data are of limited consequence is further supported by the finding of Dabós, Gantman and Fernández Rodríguez indicating a strong positive correlation between the *h*-index in Google Scholar and that in Scopus for those engaged in MGT, ultimately indicating that “if having a better bibliometric measure of individual prestige is the desire goal, then the GS [Google Scholar] h-index should be preferred" (p. 63). Since this analysis is focused on individual performance (which can be considered a form of prestige), using Google Scholar is consistent with that finding. In summary, García-Pérez indicated that Google Scholar, can "play a valuable role in the retrieval of citation records" (p. 2081), and Delgado and Repiso (2013) went as far as calling Google Scholar "the most thorough and least biased academic and scientific data source currently in existence" (p. 50). While laudatory, for this study, it is sufficient to conclude that Google Scholar provides an inclusive and accessible source of *h*-index values, which is positively correlated with alternative sources of data. Given this level of confidence in the data source, it is possible to describe in some detail how the data were collected and normalized.

Data for those identified as being engaged in CMS and MGT research were obtained from Google Scholar. A data science workflow was built in the KNIME Analytics Platform to systematically collect the *h*-index data of each author based on two separate Google Scholar search queries. The first query returned authors who were associated with CMS via the search term 'label:critical_management_studies.' The second query returned authors who were associated with MGT via the search term 'label:management.' The data collected included the author's name, affiliation, title, number of citations, and *h*-index. Given the source and the means of collection, these are considered observational, structured data. From a critical perspective, one should consider observational data "as inherently biased" (Gutman & Goldmeier, 2021, p. 46). These data were considered population data as they were the complete data from Google Scholar that meet the defined search criteria as of 8 August 2021. As such, no sample was drawn in this study. Since these data were full, complete, and exhaustive, no inferential statistical analyses were needed, and the results of the descriptive statistical analyses provided insight into population characteristics. Once obtained, the data were analyzed through a comparative analysis using standard descriptive statistic techniques and the GKL analyses were based on standard convention. A brief overview of the selected approaches is presented next.

Basic descriptive statistic techniques employed in this study include the use of Venn diagrams, boxplots, and scatter plots. The initial comparison between MGT and CMS was accomplished using a Venn diagram and was useful in establishing the degree of difference in terms of scale between the two cohorts. The comparison of the dispersion within the two groups was accomplished using boxplots. Lastly, in terms of the descriptive analysis, the relationship between the number of citations and *h*-index values was accomplished using scatter plots. Since each of these three techniques is covered adequately in introductory statistics courses (Black, 2020), and since no deviation from the established procedures was taken, no further development of the selected techniques is needed here. In terms of the GKL analysis (Goodman & Kruskal, 1954), intervals of *h*-index values were created using percentages for the CMS and MGT data, with the uncertainty assessed in the aggregate and at each faculty-rank level. The GKL was assessed both in terms of research focus (e.g., CMS and MGT) informing *h*-index interval level performance, and the converse. Since the results of the GKL for research focus informing *h*-index interval level performance were more robust, only those results were presented. With the analytic procedure complete, it is possible to summarize the keynotes from this methodology perspective.

The aversion towards positivism within CMS is one thread of longstanding skepticism. For those engaged in CMS this does not necessarily mean that one rejects analytics, but rather than one identifies and questions how power plays in its use. Google Scholar was determined to be an appropriately inclusive and accessible source of *h*-index values. The *h*-index values for CMS and MGT were obtained from Google Scholar on 8 August 2021 via the data science workflow described earlier. Once obtained, a comparative analysis was conducted using the descriptive statistics techniques of Venn diagrams, boxplots, and scatter plots, and subsequently through conducting four GKL analyses on the proportional *h*-index interval data. Collectively, these results provide a basis for understanding the relative productivity of CMS and MGT academics (as measured by the *h*-index) and provide a basis for informing one's internal narratives and external discussions of academic performance in these domains. The following section provides the empirical results of the analysis.

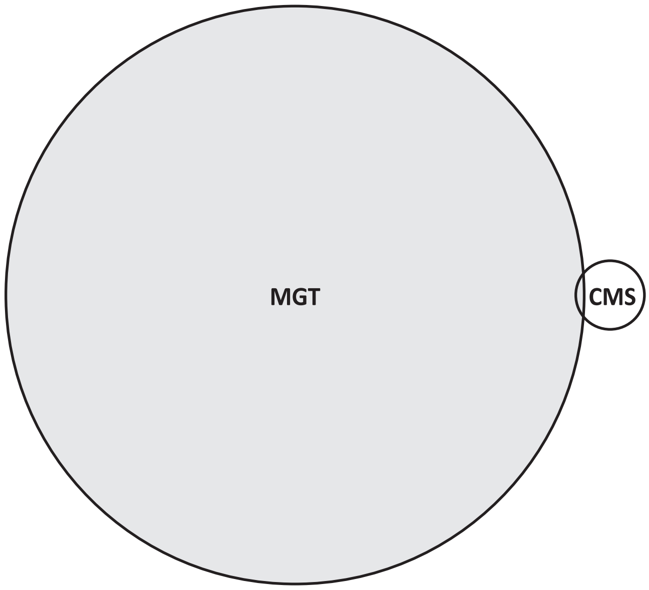
Empirical Material to Inform Academic Performance Discussions

Disconnects between the rhetoric and reality of analytics have been developed in previous sections of this paper. The limitations of analysis are serious and should not be ignored or minimized. However, results, whether discursive or empirical, provide an opportunity to inform. Using the methodology presented in the previous section, the results presented here are encouraged to be viewed as information around which one can discuss performance. To accomplish this the results of this analysis are presented through a Venn diagram, boxplot, and scatter plot. This section concludes with a summary of the results of four GKL assessments conducted on proportional *h*-index interval data at the aggregate and faculty-rank levels, along with a few concerns associated with data and a summary of findings.

In the pantheon of data visualizations, Venn diagrams occupy a position of some prominence. Given that often one learns about Venn diagrams in elementary school, they can form a foundational piece of how one thinks about and understands data and interrelationships. Venn diagrams are useful for illustrating relationships, relative size, and the degree of commonality among elements of interest. Such information can be especially useful as one develops initial conceptualizations. Figure 1 provides a to-scale representation of the relative number of observations and degree of intersection between those individuals identified as being engaged in MGT and CMS research in Google Scholar on 8 August 2021.

As visible in Figure 1, there is a significant difference in terms of scale associated with the number of MGT and CMS observations. There were 11,495 MGT and 115 CMS scholars identified in the Google Scholars database on 8 August 2021. Barely visible in Figure 1, is the small sliver of overlap between MGT and CMS. Within the data set, 5 analysts were identified as being both MGT and CMS. That CMS is comprised of significantly fewer scholars than MGT should not be surprising to those familiar with CMS. However, the lack of overlap between CMS and MGT may be somewhat less expected. While speculative, there are at least two potential explanations that could describe this phenomenon. First, since CMS is a niche area of MGT research, it would be somewhat redundant to list both CMS and MGT. Second, since there is a degree of potential antagonism between MGT and CMS, those identifying as CMS scholars might not want to also be identified as MGT scholars. Whatever the reason, the lack of significant overlap reduces the significance in terms of analytic results associated with determinations as to its accounting. For the subsequent analyses, the 5 observations in common were included only in the CMS dataset, which resulted in 11,490 MGT and 115 CMS observations. The rationale behind this treatment was that the more specific discipline (i.e., CMS) takes operational precedence over the more general discipline (i.e., MGT). With this adjustment made, it was possible to analyze the underlying dispersion associated with the CMS and MGT data. This was accomplished through a comparative boxplot analysis.

Figure 1. Venn Diagram of MGT and CMS Observations in Google Scholar

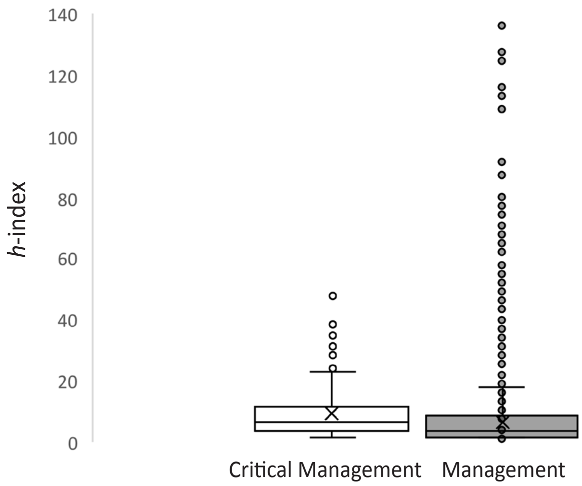


Note: CMS (white) has fewer observations than MGT (grey), with negligible intersection.

As indicated, the Venn diagram is useful for understanding the relative size and interconnection between CMS and MGT. However useful these insights are, they are incomplete. Understanding the central tendency and dispersion of the respective data is also important for context and interpretation. Such understanding is accomplished efficiently using boxplots. For relatively unincumbered data visualizations, boxplots contain many of the pieces of information associated with central tendency and dispersion which are necessary for comprehension. In addition to other relevant aspects, boxplots denote the first quartile value (Q1) which represents the point at which 25% of the observations are below, the median (Mdn) which is the point at which 50% of the observations are below, the third quartile value (Q3) the point at which 75% of the observations are below, and data points which are beyond the fence values. Those points are generally considered to be outliers in the dataset. Collectively, comparative boxplots are visually suggestive as to if a statistically significant difference exists. Figure 2 contains a boxplot comparison of the *h*-index values for CMS and MGT as contained in Google Scholar.

The CMS and MGT boxplots convey useful information in terms of central tendency and dispersion. The CMS dataset was found to have a mode of 4, Mdn = 6, M = 7 and Q3 = 11, whereas the MGT dataset was found to have a mode of 1, Mdn = 3, M = 6 and Q3 = 8 for the *h*-index. Datapoints beyond the upper fence values (i.e., the end of the *whisker* portion of the boxplot) were identified for both CMS and MGT. All the data points were retained for subsequent analyses as they are not considered outliers in a supernatural sense, but rather simply represent scholars who have atypically high *h*-index values. However, since the primary focus of this analysis is on how analyzed *h*-index data might inform the internal narratives and external discussions business academics have around the topic of performance, the presence of outliers could likely distort the point of comparison for one's relative performance. As such, much of the reported values and detailed focus was conducted and reported either on the inter-quartile data.

Figure 2. Boxplot Comparison of h-Index Values for CMS and MGT in Google Scholar

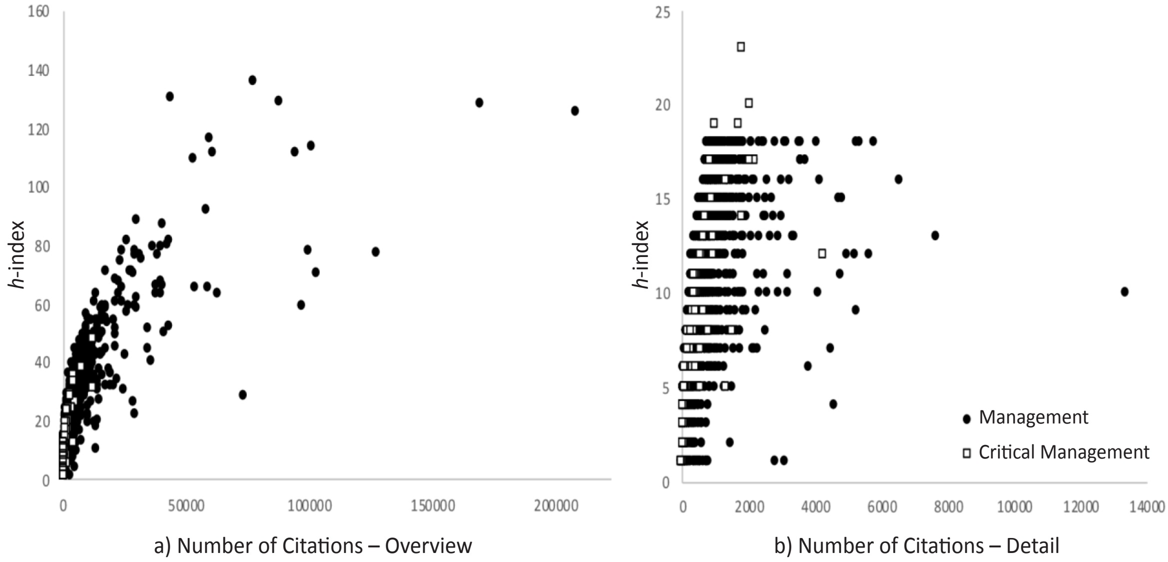


Note: Both the white (CMS) and grey (MGT) boxplots show quartile data and potential outliers.

In exploratory data analysis, scatter plots provide an opportunity to visually assess the degree to which two variables appear to be related. If a relationship is present, this does not imply causation. However, it does provide a basis from which to assess correlation and perhaps build an explanatory model. In terms of informing discussions, often awareness and acknowledgment of the correlation is sufficient for shared understanding. Figure 3 contains an overview (3a) and detailed (3b) scatter plot of the observed relationship between the number of citations and the *h*-index for CMS and MGT as presented in Google Scholar.

As indicated in Figures 3a (i.e., overview) and 3b (i.e., detail), CMS is shown to exist within the larger MGT dataset in terms of the relationship between the number of citations and *h*-index values. While Figure 3a contains all the data, Figure 3b is focused on the data which were at or below the respective upper fence *h*-index values, which were 18 for MGT and 23 for CMS. The increased granularity afforded in Figure 3b is obtained without much reduction in actual content, as Figure 3b contains 91% of the CMS and over 95% of the MGT observations. Further, Figure 3b conveys more clearly that the data analyzed are discrete rather than continuous variables. More specifically, the data in Figure 3b help to convey that a range of citation values are associated with a given *h*-index value. This is depicted visually as the horizontal lines stretching across a segment of the x-axis associated with any given *h*-index value measured on the y-axis. This relationship is obscured by the scale of the complete dataset (Figure 3a). While there is value in simply examining the data visualization, Gutman and Goldmeier (2021) explained, "the relationship found in scatter plots can reduce down to the summary statistic correlation" (p. 59). Determining correlation values provide one with a level of precision that is only broadly intuited through the visual assessment of a scatter plot. When examining the complete data set, both CMS and MGT exhibited positive correlation (based on Spearman ρ) between the number of citations and the *h*-index ($\rho_{CMS} = 0.953$; $\rho_{MGT} = 0.934$). The finding of a positive correlation between the number of citations and the *h*-index values for both MGT and CMS is consistent with previous research which established these two variables are positively correlated (Ahangar, Siamian & Yaminfirooz, 2014; Bornmann, Wallon & Ledin, 2008). Examining the interquartile ranges of these data provides additional insight. This information is presented in Table 1.

Figure 3. Overview and Detail Scatter Plots of Number of Citations and h-Index Values for MGT and CMS



Note: In both Figures 3a and 3b, black dotes denote MGT and white squares CMS.

Table 1. Interquartile Range of *h*-Index Values for CMS and MGT by Faculty Rank

Faculty Rank *(Area, observations)*	Q1	Median	Q3
Assistant Professor (*CMS, n = 11*)	3.5	5	5.5
Assistant Professor (*MGT, n = 625*)	1	2	5
Associate Professor (*CMS, n = 10*)	6.5	10	11
Associate Professor (*MGT, n = 505*)	2	6	10
Full Professor (*CMS, n = 18*)	6	16	25.5
Full Professor (*MGT, n = 1,188*)	2	7	14

As presented in Table 1, a range of values for the *h*-index might be a more meaningful way to frame one's discussions related to publication performance. The middle 50% of the observed data fall between Q1 and Q3. As such, this range might be interpreted as containing the level of performance generally considered *typical* for the respective faculty levels. At the level of assistant professor, a range of *h*-index values between 3.5 and 5.5 was observed for CMS and between 1 and 5 for MGT. For associate professors, the range of *h*-index values was between 6.5 and 11 for CMS and between 2 and 10 for MGT. Lastly, at the rank of full professor, the *h*-index values ranged from 6 to 25.5 for CMS and from 2 to 14 for MGT. In general, these results provide some context for interpreting performance as measured by the *h*-index. Whereas interquartile ranges of count data provide one way of assessing the *h*-index data, another way is to examine proportional allocations along with a standard range of values. The range constructed here is based on a three-point scale (i.e., a midpoint with one value above and below). Constructing the data in this fashion allows one to assess the relative density associated with given levels of performance, as measured by the *h*-index range. It is possible to turn attention now to the results of the GKL assessments conducted on proportional *h*-index interval data at the aggregate and faculty-rank levels. The proportional *h*-index interval data, by aggregate research area, are presented in Table 2.

Table 2. Proportional h-Index Interval Data for Aggregate CMS and MGT Faculty

Research Area/*h*-Index	1–3	4–6	7–9	10–12	13–15	16 & Over
CMS (n = 39)	12.8%	33.3%	12.8%	12.8%	2.6%	25.6%
MGT (n = 2,318)	41.5%	16.9%	12.5%	10.5%	6.1%	12.6%

As reflected in Table 2, there are a few pronounced differences between CMS and MGT in respect to the relative density of *h*-index observations. Most notably, CMS has a significant proportion (33.3%) in the h-index range of 4–6, whereas MGT has a significant proportion (41.5%) within the range of 1–3. The midrange values are relatively comparable, and then an observable difference exists with MGT having 6.1% of its observations at the range of 13–15, and CMS having 25.6% at an *h*-index of 16 and above. Examining the observed aggregate proportional *h*-index ranges by respective research focus (as reported in Table 2) using GKL, resulted in an observed reduction in prediction error ($\lambda = 0.141$). Similar observed reductions were found at the assistant ($\lambda = 0.342$), associate ($\lambda = 0.154$), and full professor ($\lambda = 0.095$) levels. The results of these GKL analyses suggest explanatory power is achieved by accounting for research focus between those engaged in CMS and MGT. Analyses of reverse constructions were performed, and in all cases those constructions performed worse than the construction presented here. This provides some further evidence that the selected research area produces an observable difference in performance as measured by the *h*-index. Whereas these values, and those contained in Table 1, may be useful for one's internal narratives and external discussions related to performance in terms of publication volume and consequence, there are a few concerns that warrant explicit development. These issues are presented next.

The first concern with the results deals with the artifactual precision of some of the values presented in Table 1. More specifically, the *h*-index is a whole number. Given the way quartile values are calculated, it is possible (as was sometimes the case here), for fractional values to be calculated. Such fractional values are artifacts of the calculation and technically reflect values that are not possible for *h*-index values. They were retained in their calculated form as a point of discussion. Second, there is some concern with the values generated at the full professor rank. This concern is mostly about the values observed at Q1. While it is possible that the observed data are accurate, there is also the potential that the label *professor* was used generically in Google Scholar, and that some of the observations in the full professor category are professors of lower, unidentified ranks. There are two reasons the consequence of this issue is considered limited. First, since this issue effects those in both CMS and MGT in a similar fashion, it isn't considered an essential concern in terms of the comparative analysis. Secondly, while this issue is potentially consequential in terms of setting the lower performance parameters at the full professor rank, there is a plausible approach that could be used to minimize this concern. In general, there is more confidence in the robustness of the values at the assistant and associate professor levels than there is for the values at the full professor level. As such, one could use a value above the Q3 value for associate professor rank as the minimum point for full professor consideration. Given that there is more validity associated with the assistant and associated professor data this might be a more beneficial approach. Those using these values for benchmarking should keep this limitation and alternative conceptualization in mind. Lastly, there is some concern as to the limited number of observations for CMS at the respective faculty levels. Since the CMS category was significantly smaller (115 observations) and since not all observations contained faculty designators, the CMS sample was relatively small (n = 11 for assistant professors; n = 10 for associate professors; n = 18 for full professors). With so few observations one should be careful not to overgeneralize the results. It should be noted that in the aggregate when all 115 CMS observations are used, this isn't a concern as that number of observations is large enough for generalizations.

The results presented here are intended to inform academic performance discussions. After adjusting for the 5 observations held in common, there were 11,490 MGT and 115 CMS observations in Google Scholar, on 8 August 2021. As these numbers suggest and as indicated in the Venn diagram (Figure 1), there is a significant difference in terms of scale between CMS and MGT. The comparative boxplot analysis (Figure 2) showed that the CMS dataset had an h-index mode of 4, a median of 6, and a mean of 7 whereas the MGT dataset had a mode of 1, a median of 3, and a mean of 6. In terms of both an overview (Figure 3a) and detail (Figure 3b), CMS was shown to exist within the larger MGT dataset in terms of the relationship between the number of citations and h-index values with both exhibiting positive correlation between the number of citations and the h-index ($\rho_{CMS} = 0.953$; $\rho_{MGT} = 0.934$). The results of the four GKL assessments suggest that accounting for research focus area (i.e., CMS and MGT) reduces prediction error of performances, as measured by the h-index, in the aggregate ($\lambda = 0.141$) and at the assistant ($\lambda = 0.342$), associate ($\lambda = 0.154$), and full professor ($\lambda = 0.095$) levels. The values for the interquartile range and median for each faculty level were presented for CMS and MGT along with some concerns associated with the data and interpretation. To facilitate the incorporation of these results into one's academic performance discussions, some summary, limitational, and extensional perspectives are provided in the following section of this paper.

Conclusion

Analytic results can inform the internal narratives and external discussions of those who are critical of its epistemology and ontology (Heath & Jackson, 2013). Even if one can eschew the analytic discursive frame in one's internal narratives, one has little control over the types of positivist material one's interlocutor brings to a discussion. When there are asymmetric power dynamics involved, as is the case of academic performance reviews, such a framing may be unavoidable. Consequently, it is pragmatically useful for those critical of the empirical tradition to understand the analytic approach and the types of results it generates so that one can participate more strategically and effectively in the discussion. To that end, this study compared the *h*-index values between those identified in Google Scholar as engaged in CMS research and those engaged in MGT. The results of this study were found to be robust and consistent. While robust, there are limitations associated with this study that warrant discussion.

As previously indicated, the faculty rank field in Google Scholar was found to be incomplete, and at the full professor level, ambiguous. From a comparative analysis perspective, there is little concern of bias as these limitations effect CMS and MGT data similarly. Another limitation of this study was that a single data source was used. While Google Scholar has the benefit of being popular and accessible, a single data source has inherent limitations. Further, in terms of the data, the study is limited by its use of observational data. While it would be impractical and unethical to subject faculty to a controlled experiment to test hypotheses that could limit their careers, it is important to acknowledge the constraints which arise due to the nature of observational data. Lastly, this study compared only CMS and MGT. There are a variety of fields within business schools. Examining performance across a spectrum of business disciplines would provide additional context for interpretation and discussion. While each of these limitations is serious, collectively they do not undermine the utility of the findings.

Of the limitations of this study listed, only two hold ample possibilities as extensions to this research. One possible extension of this study would be to incorporate alternative data sources. Potential sources of academic information are Microsoft Academic, WOS, and Scopus. While the results generated here based on Google Scholar are significant, using alternative data sources would indicate further the degree to which these results are robust. A second extension of this study would be to incorporate additional business disciplines. It is certainly feasible that disciplines within business schools have dissimilar expectations in terms of academic publication volume and citations. As a hypothetical example, perhaps those in accounting are expected to conduct field audits in lieu of publications. If this were the case, accounting professors might reasonably have lower *h*-index values than those engaged in MGT. Extending this research to include other business disciplines would add context. The extensions offered here hold the potential to enhance understanding of academic performance as measured by the *h*-index. It is beneficial in terms of narratives and discussions, to conclude by reiterating the contribution of these results.

Internal narratives and external discussions contain a degree of intentionality. While one can rationally, and possibly easily, stake critical stances against analytics, it is constructive to admit its ubiquity in both academics and business. In the asymmetric power dynamic between senior and junior faculty, quantified performance assessments could be unavoidable as both the basis of measurement and the point of discussion. Such a movement is inherently constraining. The results of this study suggest that at each faculty rank, those engaged in CMS have a higher *h*-index than those engaged in MGT and that accounting for the research area reduces the prediction error of performances, as measured by the *h*-index. It may be pragmatically useful to incorporate these findings into one's performance discussions, even if one is skeptical of its underlying epistemology so that those engaged in critiques of MGT and organizational power can continue to advance and produce research of both volume and effect. Some may even consider this goal critical.

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