Value Creation of Big Data Utilization: The Next Frontier for Productive Scholarship among Filipino Academics

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Abstract: Research productivity plays an important role in the prestige and reputation among higher education institutions. However, the time spent to do research among Filipino academics is the most pressing issue since they can barely meet the requirement for research productivity. Further, the lack of time for data gathering aggravated the drawbacks for research productivity. Data gathering is at the core of almost all research activity, the absence of factual and reliable data will lead to an invalid and illogical inference. In research years, there has been a massive agglomeration of data in large volumes coming from diverse sources pertaining to almost all facets of human activity which is worthy of investigation- known today as Big Data. This research has two (2) main objectives; the first is to find out the underlying reasons why Filipino academics are not enthusiastic to do research. The second is to evaluate the value of big data utilization for research productivity based on the assessment of the faculty members. This research used the Rasch model to measure the responses of Filipino academics with regards to their reasons for not doing enough research work as well as on their assessment for value creation of big data utilization using a polytomous item response selection scale.

Keywords: *Research productivity, big data, Rasch model, productive scholarship, academic productivity.*

Introduction

Productive scholarship among majority of Filipino academics is a scant reality. A ranked lecturer or a ranked professor in the Philippines trails behind with other ASEAN academics in terms of research publications. This situation explains why, that even those Philippine higher education institutions (HEIs) that has landed in the top 500 of the Quacquarelli Symonds (QS) World University Rankings continues to lose their foothold and sliding down from their previous positions. Although in the Philippines, HEI ranking is not so much of an issue among academics, yet it places a great importance in the totally of educational quality of a country vis-vis reputation and prestige. Research productivity among academics is one of the primary outcomes and determinant of HEI standing all over the world (Cummings & Shin, 2014). Further, it has a significant impact on the quality of graduates an HEI is producing as perceived in the international standard of education. Having said about ranking, research productivity plays an important and pivotal role to increase the level of prestige and reputation among HEIs (Brew, 2003). However, even if there has been an annual release of ranking results from the QS and other ranking bodies, the Philippine HEIs are still struggling to maintain their position- for those that made it to the top 600. For the rest, it is still a far cry to be included in the top 1000.

It has been an acceptable fact and reason both from the point of view of the policy makers and from the Philippine academia in general that majority of higher education institutions in the Philippines have their academics situated at a disadvantage position due to low research expenditures, lack or low research productivity incentives and most of all the teaching-research time balance activity (CHED, 2015).

Majority of the Philippine academics are into teaching-focused activity with little or no time for doing research or productive scholarship. Since the remuneration and financial source comes mainly from teaching, Filipino academics

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would find it difficult to strike a balance between teaching and doing research. Over and above the teaching job, academics are faced with substantial amount of paper works or shadow works (Lambert, 2011) which also take so much of their time, some of these works are even brought at home just to be finished and meet the submission deadline. Filipino academics struggling to have an economic survival must teach at least a minimum of 18 hours per week. Some HIEs would give 24-hour per week teaching loads in the undergraduate level with normally two or three subject preparation. Even with a 24-hour week teaching load, this doesn't mean that an academic is already well-off in terms of his economic standing. The economic well-being of academicians depends on their hourly rate or on their monthly compensation. Despite having so many excuses to do research, it is a personal responsibility and accountability of a faculty member to become productive in his or her academic career other than just merely teaching (Brew & Lucas, 2009). The 21st century academic environment necessitates faculty members to carry out the function of doing research (King, 2004). Faculty members that are well-exposed to research activities also have higher self-efficacy in their instructional or teaching functions. Research activity enhances the breadth and depth of knowledge, skills and competence of academicians. This will in turn improves faculty members' competence to properly supervised research projects of their students may it be in the undergraduate or graduate level (Lindsay, Breen & Jenkins, 2002).

Although recently, research productivity has become one of the criteria for ranking as well as one of the bases for salary increase, majority of Philippine HEIs have a long way to go for improving their research incentive systems. In the standard practice of tenure and promotion in the academia (Mason, Casey & Betts, 2010), research productivity should be one of the basis of faculty performance (Goldhaber & Hansen, 2010) aside from teaching performance (Coulter & Weins, 2002), however many Philippine HEIs cannot strictly impose such criteria. Majority of the faculty members are not into research activities. Imposing a publish or perish policy will result to the scarcity of academics that are qualified to teach in the tertiary education level. In general, the time spent to do research among Filipino faculty members is the most persistent issue since they can barely meet the requirement for research productivity and attending to their classes doing their lectures. Further, research unproductiveness has been aggravated by pressing issues such as the time that should be spent for an exhaustive review of related literatures and the time for data gathering is very minimal if not impossible to do so. Taking into consideration the demand of work-life balance is a stressful task for Filipino academics. Caught in a quandary of economic survival and the imperative to carry out a productive scholarship work is big challenge to gain a successful academic career. In the long-run, Filipino academics has to face the reality that research activity is inevitable and it has been a recent trend that scholarly productivity is one of the gold standards of a successful career in the academia (Shauman & Xie, 2003).

Productive Scholarship and Research Productivity

Productive scholarship or also referred to as research productivity pertains to the entire domain of research activities that includes publications of books, journal articles, conference presentations and speakership and receiving grants and funding for research activities (Nguyen & Kloppper, 2014). Empirical investigations have pointed out that the environment of an academic which he or she belongs have significant impact on research productivity (Gregorutti, 2008). According to White, James, Burke and Allen (2012), a good working environment is a place where academics are provided with the opportunities to access and avail resources and support to carry-out their productive scholarship activity.

Underlying Factors of Research Unproductiveness

Research unproductiveness does not occur simply because academics do not want to carry out research activities. There are several underlying reasons for such phenomenon which has already been established by previous body of knowledge within this sphere of investigation. White et al. (2012) has proposed two reasons for research unproductiveness. The first reason is attributed to the individual level factor and the second is related to the situation level factor. The individual level is further specified under four considerations: low conscientiousness, low-value for research activity, low time management skills and lower attained rank. On the aspect of situation level factor, five variables have been identified: less research support, less or no doctoral student support, no time available for research, research is not a top priority of the university.

Self-efficacy and Research Productivity

Research productivity is an important criterion in the overall measure of faculty performance and consequently leads to merit increases, promotion and tenure (Hesli & Lee, 2011; Shepherd, Carley & Stuart, 2009; Long, Bowers, Barnett & White., 1998; Zucker & Darby, 1997). For an academic that is conscious of his or her career growth and personal development would definitely place a considerable value on the intrinsic and extrinsic rewards that will be received from doing research (Chen, Gupta & Howshower, 2006) such as a better salary raise during ranking and peer recognition (Markham, Dow & McKee, 2002). Moreover, the personal attributes of an academic and his or her behavior towards doing research is also a major consideration. Personality attributes plays an important role in a person's self-efficacy (Bandura, 1977, 1994, 1997) and it applies in the case of doing research. Academicians with higher self-confidence of doing research also tend to have higher levels of self-efficacy (Aslan & Agiroglu Bakir, 2017). Self-efficacy

can be deemed to influence an academic's action to produce a desirable level of scholarly research output knowing his or her capabilities to do so which he or she exercises over prevailing circumstances surrounding his or her life. Self-efficacy plays a crucial role in the professional performance of a faculty member (Kormaz & Unsal, 2016) particularly in doing research activities. The personality of an academic is also regarded as a main source of individual's intrinsic motivation (Barrick, Stewart & Piotrowski, 2002) with regards to the intention to carry out his or her obligation as an academic to produce research outputs.

The personal motivation of an academic to carry-out productive scholarship activities based on some intrinsic and extrinsic rewards can be explained by a construct known as expectancy theory (Vroom, 1964). It is grounded upon the classic work of Vicor Vroom (1964) which actually started way back in 1930 by Tolman and Honzik, setting forth key assumptions that a person is motivated to the degree that he or she believes that his or her effort will lead to acceptable performance (expectancy) and such performance will be rewarded (instrumentality), and the value of the rewards is highly positive (valence) (Lunenburg, 2011; Chen & Fang, 2008). This relates to the overall expectation (Lunenburg, 2011) of an academic that doing research will produce a relatively better outcome for his or her career in the future such as getting tenured, receiving a promotion, getting a salary raise and peer recognition among others (Chen et al., 2006). The underlying incentives for doing research usually tied to compensation and other rewards (Berger, 2009) are powerful motivation for productive academics in producing scholarly works.

Making Sense of Big Data for Research Productivity

Despite reluctance and idleness of some Filipino academics to engage in research activities, it has been a global trend that research productivity is a measure of promotion, tenure and salary increase (Kotrlik, Barlett, Higgins & Williams, 2002; Bloedel, 2001). Sooner, Philippine HEIs cannot help but to follow the norm of global academic practice (Hartman, 2011, 2010; Kritz, 2006; Tullao, 2003) and their faculty members that lag behind in terms of productive scholarship output will become vulnerable to the ubiquitous publish or perish tradition (van Wesel, 2016; Miller, Taylor & Bedeian, 2011; Qiu, 2010; Neill, 2008; Savla & Hawley, 2004; Wilson, 1942).

One of the major reasons among academics why they are not producing substantial research outputs is their lack of time for data gathering which often encounter challenges when obtaining information from participants for a proposed study (Rimando, Brace, Namageyo-Funa, Parr & Sealy, 2015). A considerable number of recent researches have pointed out that data collection among researchers posed significant problems and challenges (Bourne & Robson, 2015; Bonevski et al., 2014; Hebert, Loxton, Bateson, Weisberg & Lucke, 2013; Dearnley, 2005; Johnson & Clarke, 2003; Easton, McComish, & Greenberg, 2000) as well as previous works (Kenney & Macfarlane, 1999; Brenner, 1981). The problem of data gathering further aggravates when a researcher is studying vulnerable groups (Geldens, 2002) and the selection of research instrument that is reliable to measure the phenomenon of interest (Bastos, Duquia, Gonzalez-Chica, Mesa, & Bonamigo, 2014). Also, the subjects' perplexing behavior during data gathering poses a significant challenge to a researcher (Anyan, 2013).

Data gathering indeed is at the core of almost all research activity. With the absence of factual and reliable data, either quantitative or qualitative in nature, a researcher has no basis which he or she can draw a valid and logical inference. Reliable data collected from ethical methods has been used in meaningful ways that have benefited humanity. In research years, there has been an immense agglomeration of data in large volumes coming from diverse sources (Kuo & Kusiak, 2018) pertaining to almost all facets of human activity which is worthy of investigation. In the old framework of research perspective, Big Data is usually referred to as secondary data gathered from institutional repositories and other researchers (Cnossen, 1997) as compared to primary data directly gathered by a researcher through field work, although traditional teachers of research methodologies also advised their students to consider the review of secondary data (Novak, 1996) to enrich their understanding of their research topic.

The concept of big data is not really new as most academics would think. Glaser (1963) has been suggesting that secondary analysis carried out by an independent researcher could lend new strength to the body of fundamental social knowledge. Successive movements on the use of such initiative were carried on by Corti and Thompson (1995, 1998), Hinds, Vogel and Clarke-Steffen (1997), Heaton (1998), Fielding (2004), Long, Sque and Addington-Hall (2008), Smith (2008) and Sutehall, Sque and Hall (2010) among others.

As the way of doing research undergoes a systemic revolution so as the way data gathering and collection. Big data has replaced the old perspective which used to be viewed as secondary data. In recent years due to the advent of more efficient information and communication technologies and platforms, the utilization of big data for research and decision making has grown tremendously both in academia and industry (Zook et al., 2017). This phenomenon has fostered a dramatic change in the process of data gathering procedures that challenges the former paradigm. Moreover, it offers some opportunities for academics to become more efficient (Jorm, 2015) in their data gathering due to the ever-present availability of data from institutional repositories. This gives a convenient way for academics to manage their time in hunting for viable data since knowledge mapping in the big data architecture is more efficient (Manyika et al., 2011).

Research Objectives and Context

This research has two main objectives. First, is anchored upon the investigation of research unproductiveness among Filipino academics. The purpose of which is to uncover the underlying reasons why Filipino academics are reluctant to do research in spite the need to do so.

The second objective is to uncover the value of big data utilization for research productivity. Stated in the premise of this research is the consideration that data collection phase is one of the most tedious process due to the difficulties of field work especially for those researchers working out on primary data. Hence, a logical alternative for data gathering is to collect data from readily available sources that does not require too much field work at the same time reducing the intensity to comply to the rudiments of ethical consideration especially if the researcher is working with human subjects. Big data on this regard holds the promise to lighten the work for data gathering while maintaining the quality of the research process as well as its output.

Methodology

This research used the Rasch model (Rasch, 1960, 1980) to measure the responses of Filipino academics with regards to their reasons for not doing enough research work as well as on their assessment for value creation of big data utilization using a polytomous item response selection scale (Andrich, 1978; Masters, 1982).

Scoring of responses

An ordinal 5-point semantic differential scale was used to solicit responses from the respondent academics. The responses of the academics (perspective response) are considered as latent variables that derives from the combination of some other independent latent variables (reasons for not doing enough research work). The known variables (reasons for not doing enough research work), generally expressed by an ordinal rating are observed through the administration of a survey questionnaire to the respondent academics in order to measure those dimensions.

Research Instrument

This research utilized the 12-item factor to solicit responses among Filipino academics with regards to their underlying reasons for not doing enough research work. The reliability index of the instrument was rated at 0.92 tested at the local setting. The items stipulated within the instrument correspond to the work of Fawzi and Al-Hattami (2017) which also aims to determine responses with regards to reasons for not writing and publishing much research papers.

On the other hand, the ten (10) item instrument to assess the value creation for big data was crafted through the acclimatization of several previous researches. The works of Sanchez-Martinez and Munizaga (2016), Kubina, Varmus and Kubinova (2015) and that of the McKinsey Global Institute (2011) had substantially provided the framework to construct the instrument for value creation of big data utilization for research productivity.

Respondents and Sampling Technique

Full-time faculty members from Philippine's public and private HEIs were purposively chosen to answer the research instrument. The respondent academics have ranks such as professors, associate professors, assistant professors and instructors. All are either in tenured or permanent status in their respective HEIs. There was a total of 100 faculty-member respondents that have participated in the study. The age range of the respondent academics spans from 27 years old for the youngest and 60 years old for the oldest and their teaching experiences spans between four years to 35 years.

Results and Discussions

Table 1 shows the item response analysis for underlying reasons for not doing enough research work measured on logit scores. Items ranked 1.5 ('lack of time' and 'teaching workload pressure') possessed the lowest logits which indicates that the two (2) items are the most compelling reasons among respondent academics why they are not doing enough research work. The infit and outfit diagnostics (0.84 and 0.88 respectively) on the other hand suggests that there is an overfit in estimating the construct for underlying reasons for not doing enough research work. Reliability values closed to 1.0 is considered to have an internal consistency (Oon, Spencer & Kam, 2017). In Rasch measurement, fit statistics with the range of 0.9 to 1.20 are deemed to have the right fit. Lower values tend to suggests overfitting while higher value indicates under fitting. On this regard, the items in Table 1 have measured the underlying reasons for not doing enough research work way beyond the statistical reliability expectation.

The infit and outfit diagnostic statistics (0.84 and 0.88 respectively; Table 2) supports the fitness of the construct for the underlying reasons for not doing enough research work.

Table 1: Item Response Analysis for underlying reasons for not doing enough research work

Rank	Item	Measure	Model S.E.
1.5	1. Lack of time	-76.87	18.46
1.5	2. Teaching workload pressure	-76.87	18.46
3	3. Other paper works pressure	-64.14	10.44
4	4. Lack of funding and support	-16.23	5.88
5	5. Family obligations' pressure	23.67	21.86
6.5	6. Lack of motivation and interest	47.09	10.37
9	7. Lack of literature resources	66.87	5.44
10	8. Lack of competence and knowledge	79.15	4.72
11	9. Lack of confidence to do research	103.29	5.91
6.5	10. Lack of proper research orientation	47.09	10.37
8	11. Lack of networking and collaboration among colleagues	63.69	5.87
12	12. Age related factor	149.54	3.80
	Mean	28.86	10.13
	P.SD	70.13	5.93

Table 2: Infit and Outfit Diagnostics for underlying reasons for not doing enough research work

Item	Infit		Outfit	
	IMNSQ	ZSTD	OMNSQ	ZSTD
Mean	0.84	-0.1	0.88	0.0
P.SD	0.36	0.8	0.76	1.1
		Item Reliability 0.97		

Table 3 shows that the item pertaining to: 'big data has lower risk on privacy issues and ethical compromised', has the lowest logit (3.84) which signifies that this item is the top most consideration for value creation for big data utilization. Second most consideration that big data can add value for research is the item: 'big data will usher in new analytical tools that are more sophisticated and robust than traditional statistical methods' having a logit measure of 19.06. The infit and outfit diagnostic statistics (Table 4; 1.01 and 1.14 respectively) also indicates that the construct for value creation for big data utilization are well within the accepted limits of Rasch measurement convention.

Table 3: Item Response Analysis for value creation for big data utilization

Rank	Item	Measure	Model S.E.
1	1. Big data has lower risk on privacy issues and ethical compromised.	3.84	18.68
9	2. Big data will enable researchers to access public domain databases at no or minimal cost.	66.05	6.72
4.5	3. Big data will enhance the process of data visualization methods that can be used for better presentation.	52.28	7.14
8	4. Big data will empower researchers to become more resourceful in data mining and data utilization.	57.09	6.82
3.5	5. Big data can offer more informed and objective inferences.	40.16	8.77
3.5	6. Big data can foster greater knowledge expansion from the bulk of unexplored information.	40.16	8.77
10	7. Big data can be used to create more detailed analysis for almost any type of study.	70.65	6.91
4.5	8. Big data enables deeper analytical investigation by pointing to hidden patterns of relationships within the massive volume of information.	52.28	7.14
4.5	9. Big data can facilitate more rapid decision-making and scientific breakthroughs.	52.28	7.14
2	10. Big data will usher in new analytical tools that are more sophisticated and robust than traditional statistical methods.	19.06	12.14
	Mean	45.38	9.02
	P.SD	19.54	3.58

Table 4: Infit and Outfit Diagnostics for value creation of big data utilization

Item	Infit		Outfit	
	IMNSQ	ZSTD	OMNSQ	ZSTD
Mean	1.01	0.0	1.14	-0.1
P.SD	0.58	1.4	1.37	0.9
Item Reliability 0.70				

Data Availability

The quantitative data used to support the findings of this study are available from the corresponding author upon request.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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