RESEARCH DATA SHARING PRACTICES OF ACADEMICS IN NIGERIA: THE EFFECTS OF ORGANIZATIONAL CULTURE

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RESEARCH DATA SHARING PRACTICES OF ACADEMICS IN NIGERIA: THE EFFECTS OF ORGANIZATIONAL CULTURE

ABSTRACT

Research data sharing was perceived differently among academics worldwide. Even though general view of data sharing is essential in enabling academics to have ease in conducting research, but effort, time and energy involved in data sharing practices made it difficult to some researchers particularly in periphery countries such as in Nigeria landscape. Therefore, this study was conducted with the following purposes: i) to examine how does Nigerian academic community perceive data sharing, ii) to investigate factors that influence academics' data sharing practices and to see the differences of data sharing between sciences and social sciences scholars. This study was conducted based on the theory of organizational culture in viewing the way academics share their research data in the lens of collective values, beliefs and principles of organizational members. Quantitative research approach was used for collecting data by means of semi structured interview and survey questionnaires. Data was gathered from academics in 5 Nigerian universities. A total of 22 academics were interviewed to investigate their perception, motivation and perceived risk of research data sharing. The interview was analyzed using thematic analysis technique. The finding from the interview revealed discipline receptive, funding agencies, and journal publishers as some of the ways academics become aware of data sharing practices and academics understood research data sharing differently with majority seen it as a progress to research while few on the opinion that is of no use. Cloud source repository and personal websites are identified to be some of the data sharing practices' platforms. Expecting more citations, academic promotion, recognition, monetary incentives are acknowledged to be some of the motivational factors for data sharing practices. Furthermore, data privacy and cultural orientations are realized to be some of the risks involved in data sharing practices. The findings from the interviews were used in the development of the survey instrument to suit more appropriately Nigerian context which is to investigate factors that could influence academics in Nigeria on research data sharing. The survey questionnaires were disseminated randomly to 378 academics in Nigeria using stratified sampling technique. Responses from the survey questionnaire were analysed using the Structural Equation Model (SEM) SmartPLS software. The survey findings indicated three categories of factors namely, i. personal attributes that comprised effort expectancy, legitimate concern, beneficence, conditions for data sharing and expected rewards, ii. Organizational attributes that involved research funders, perceived pressure by journal, data repository, organizational structure, infrastructure and policy and guidelines, iii. Social attributes that consist of community culture and discipline norms influence data sharing practices among Nigerian academics. This study hypothesized 13 relationships and the path coefficient analysis shown all hypotheses supported considering a p. value <0.05. The discussion on influence of academics' data sharing practices revealed nine variables had a significant positive coefficient (expected rewards (β=0.235, $p<0.05$), beneficence (=β 0.157, $P<0.05$), discipline norms ($\beta = 0.169$, $P<0.05$), data repository ($\beta = 0.082$, $P<0.05$), research funders ($\beta = 0.034$, $P<0.05$), infrastructure ($\beta = 0.039$, $P<0.05$), perceived pressure by journal (β =0.096, $P<0.05$), organizational structure (β =0.094, $P<0.05$) and policy/guidelines ($\beta = 0.049$, $P<0.05$). with four having negative significant coefficient (conditions for data sharing ($\beta = -0.098$, $P<0.05$), legitimate concern (β =-0.130, $P<0.05$), community culture (β =-0.096, $P<0.05$) and effort expectancy (β =-0.110, P,0.05). The data analysis demonstrated differences between sciences and social sciences academics in their data sharing practices in which academics from the sciences were more willing to share their research data as compared to academics in social sciences counterparts. The findings of this study is important to provide more understanding on the research data sharing practices particularly among academics in Nigeria where the community culture and ICT infrastructure is different from other part of the world. Three contributions are highlighted comprising body of knowledge by addressing issues related to awareness, understanding, familiarity, motivations and risks involved in data sharing among academics. Theoretically by assisting in discovering new items such as community culture and infrastructure and practice by encouraging the participation of academic towards data sharing practices particularly in Nigeria and or the worldwide.

Keywords: Research Data Sharing Practices, Academics, Nigeria, Organizational culture

AMALAN PERKONGSIAN DATA PENYELIDIKAN DALAM KALANGAN AHLI AKADEMIK DI NIGERIA: KESAN BUDAYA ORGANISASI

ABSTRAK

Ahli akademik di seluruh dunia mempunyai persepsi berbeza mengenai perkongsian data penyelidikan. Secara pandangan umum, perkongsian data adalah penting dalam memudahkan penyelidikan oleh para akademik, namun sesetengah faktor seperti usaha, kekangan masa dan tenaga yang diperuntukkan dalam amalan perkongsian data dapat menyukarkan sesetengah penyelidik khususnya di negara terpinggir seperti Nigeria. Oleh yang demikian, kajian ini dijalankan bertujuan untuk: i) mengkaji persepsi komuniti ahli akademik Nigeria terhadap perkongsian data, ii) mengkaji faktor-faktor yang mempengaruhi amalan perkongsian data akademik dan untuk mengkaji perbezaan perkongsian data di antara para cendekiawan dalam bidang sains dan sains sosial. Kajian ini dijalankan berdasarkan teori budaya organisasi melalui praktis ahli akademik dalam berkongsi data penyelidikan mereka dari segi nilai kolektif, keyakinan dan prinsip anggota organisasi. Pendekatan penyelidikan kuantitatif telah digunakan untuk mengumpul data iaitu secara temubual separa berstruktur dan tinjauan soal selidik. Data telah dikumpulkan daripada ahli akademik di lima (5) buah universiti di Nigeria. Sejumlah dua puluh dua (22) ahli akademik telah ditemubual bagi mengkaji persepsi, motivasi dan risiko yang diperolehi daripada perkongsian data penyelidikan. Temubual tersebut telah dianalisa menggunakan teknik analisis tematik. Hasil daripada temubual mendapati penerimaan disiplin, agensi pendanaan, dan penerbit jurnal merupakan beberapa cara ahli akademik menyedari tentang wujudnya amalan perkongsian data. Selain itu, pemahaman ahli akademik mengenai perkongsian data penyelidikan juga berbeza di mana majoriti melihatnya sebagai kemajuan terhadap penyelidikan manakala sebilangan yang lain berpendapat perkongsian data penyelidikan sebagai tidak penting. Laman sesawang seperti repositori perkongsian terbuka dan laman sesawang peribadi telah dikenal pasti antara sumber utama amalan perkongsian data. Beberapa faktor penarik juga dikenal pasti di dalam amalan perkongsian data seperti mengharapkan lebih banyak penghasilan sitasi, promosi akademik, pengiktirafan, dan insentif kewangan. Di samping itu, privasi data dan orientasi budaya juga dikenal pasti antara risiko dalam amalan perkongsian data. Penemuan dalam temu bual juga telah digunakan dalam membangunkan instrumen tinjauan soal selidik supaya dapat memenuhi konteks di Nigeria iaitu untuk mengkaji faktor-faktor yang dapat mempengaruhi ahli akademik di Nigeria dalam perkongsian data penyelidikan. Tinjauan soal selidik telah diedarkan secara rawak kepada 378 ahli akademik di Nigeria menggunakan teknik pensampelan berstrata. Maklum balas daripada tinjauan soal selidik telah dianalisa menggunakan perisian ‘SmartPLS’ *Structural Equation Model* (SEM). Hasil tinjauan kaji selidik mendedahkan tiga (3) kategori faktor iaitu i) Atribut peribadi yang terdiri daripada tanggapan usaha, kebimbangan yang sah, kesedaran, syarat-syarat perkongsian data dan faedah yang dijangkakan; ii) Atribut organisasi yang melibatkan agensi pembiayaan, penerbit jurnal, struktur organisasi, repositori data, infrastruktur dan dasar serta garis panduan; iii) Atribut sosial yang terdiri daripada budaya komuniti dan norma disiplin yang telah mempengaruhi amalan perkongsian data di kalangan ahli akademik di Nigeria. Kajian ini telah menjanakan hipotesis daripada tiga belas (13) hubungan dan ‘path coefficient analysis’ menunjukkan semua hipotesis disokong dengan mempertimbangkan nilai p. <0.05. Perbincangan mengenai pengaruh amalan perkongsian data akademik telah menunjukkan Sembilan (9) pembolehubah yang mempunyai ‘significant positive coefficient’ yang signifikan *(expected rewards ($\beta=0.235$, $p<0.05$), beneficence (=β 0.157, $P<0.05$), discipline norms ($\beta = 0.169$, $P<0.05$), data repository ($\beta = 0.082$, $P<0.05$), research funders ($\beta = 0.034$, $P<0.05$), infrastructure ($\beta = 0.039$, $P<0.05$), perceived pressure by journal ($\beta =0.096$, $P<0.05$), organizational structure ($\beta =0.094$, $P<0.05$) and policy/guidelines ($\beta = 0.049$, $P<0.05$). with four having negative significant coefficient (conditions for data sharing ($\beta = -0.098$, $P<0.05$), legitimate concern ($\beta =-0.130$, $P<0.05$), community culture ($\beta =-0.096$, $P<0.05$) and effort expectancy ($\beta =-0.110$, P,0.05).* Analisis data menunjukkan terdapat perbezaan pandangan di antara ahli akademik daripada bidang sains dan sains sosial dalam amalan perkongsian data. Ahli akademik daripada bidang sains lebih terbuka untuk berkongsi data penyelidikan mereka berbanding ahli akademik daripada bidang sains sosial. Penemuan kajian ini adalah penting dalam memberi lebih pemahaman tentang amalan perkongsian data penyelidikan khususnya di kalangan ahli akademik di Nigeria kerana budaya komuniti dan infrastruktur ICT mereka sangat berbeza berbanding dengan negara-negara lain di serata dunia. Tiga (3) sumbangan telah diketengahkan dalam pengorganisasian pengetahuan iaitu dengan menangani isu-isu yang berkaitan dengan kesedaran, pemahaman, kebiasaan, motivasi dan risiko-risiko yang terlibat dalam perkongsian data di kalangan ahli akademik. Secara teorinya, dengan penemuan pengetahuan baru seperti budaya masyarakat dan infrastruktur serta dipraktikkan oleh akademik, ini dapat menggalakkan penyertaan ahli akademik dalam mengamalkan perkongsian data khususnya di Nigeria serta di serata dunia.

Kata kunci: Amalan Perkonsian Data Penyelidikan, Ahli Akademik, Nigeria, Budaya organisasi

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CHAPTER 1: INTRODUCTION

1.1 Introduction

The preface to this research commences with a brief outline of this study which is presented in six chapters. The chapter overview ponders and enlightens this thesis from academic's viewpoints and the urged for the interdisciplinary field of study. The research background is another part that discusses the whole research setting from the area of this study to the in-depth of research data sharing and academics. The motives behind the conduct of this study "perceptions and practices of research data sharing study was also presented. Nevertheless, problem statements are made known to identify the research gap for this precise study. Thus, the research problems are pleased by generating research objectives to meet the goal of the current study. In justifying this, current research aim is evidently specified in research objectives. Subsequently, is to suggest the suitable research questions to response and address the research objectives. Also, the worth and contributions of this study are being deliberated under the significance of the study. It is clearly shown that this study has huge significance to universities and other related organizations. Some relevant definitions of terms for this research are presented then followed by organization of thesis and finally concluded the section with a brief but meaningful summary.

1.1.1 Overview

This section deemed it desirable to start by asking a question "what is the future of sharing research data? Generally, research is transiting towards data intensive in academia. The research data sharing perceptions and practices of academics describe the futurist's impacts on researchers' participation. A genius and successful researcher must indicate interest in maintaining research data freely available. The amount of interest and understanding of research data sharing will generate a high level of practices and involvement among researchers. The intention of every researcher is to conduct a good research that can easily be replicated. It is therefore possible to do this through participation and collaboration with peers in the process of conducting research. Even though, sharing of research data differs from one discipline to another, it promotion will encourage scholars' collaboration and refining a data sharing framework across all disciplines in universities. Researchers as a matter of earnestness must come together and share research data for research progression.

The recent advancement of information and communication technology (ICT) is another avenue that aids the researchers in data sharing without difficulties. The present research data intensive situation is an opportunity for the researchers to encourage diversity of analysis and opinions, promote research novel and facilitate the education of fresh scholars. At the present, data sharing facilitates data driven replication researches and permit to handle new research questions on the basis of secondary data.

The aforementioned indicates that there is need on the part of academics to fully participate in data sharing practices and this and other reasons necessitate the conduct of the present study on research data sharing.

1.1.2 Background of the study

"Data is considered to be a valuable item which would last much longer than the systems themselves'. It's hard to envisage the influence that you might have when numerous diverse kinds of data are available. -Tim Berners-Lee, Father of the Worldwide Web. The above quotes highlight how significant is it to have data easily accessible and also confirm the value that should be attached research data sharing particularly among academics.

Open science is an unruly phenomenon which is presently evolving all over the globe particularly in Europe, America and Asia. Open science provides variety of changes including Openness and collaboration related to socio-cultural and technological transformation, showing how research is designed, evaluated and achieved. Open data, data sharing, open access, open peer review methods, and other academic engagements are irreparable developments that are influencing all researchers' activities with the prospect of quicken the research cycle. Several institutions and policy makers are embracing open science strategies to aid the notion of open access to open research data (Zenk-Möltgen, Akdeniz, Katsanidou, Naßhoven, & Balaban, 2018). The value of open data is gargantuan in terms of the when it comes to reproduction of research outcomes (Agosti, Ferro, & Silvello, 2018), the salvage and retrieve of old data (Moss, Cave, & Lyle, 2015), and the intensification of efficiency as well as regenerating of research data in academics (Gregory, Cousijn, Groth, Scharnhorst, & Wyatt, 2018).

Similarly, the assurance of open science is to permit healthier collaboration through academic environment, government and also public sector (Tannenbaum et al., 2018). Recently, scholars from diverse fields of studies have started embracing data sharing strategies to encourage openness and reproduction. Thus, making research data freely available is essential to enable research progression. Practically, replication is not manifesting across academic environment (Zenk-Möltgen et al., 2018). Although data sharing performs an increasingly important role in empirical research, researchers in respective of their disciplines seem not to have been appreciating. However, does the academic environment have a clear perception of the concept "open science"? Numerous investigations reveal the absent of awareness of open science among people (Ramjoué, 2015), as a result of inadequate recognized explanation of the term "open science" (Pitrelli & Arabito, 2015; Ramjoué, 2015).

Open science is a developing area in research that has no widespread theoretical framework in the academic cycle. However, certain research teams conclude by describing open science to be; knowledge (translucent knowledge, reachable knowledge, collective knowledge, and cooperative knowledge (Vicente-Sáez & Martínez-Fuentes, 2018). As transparent knowledge open science serves as a “transparency of knowledge production” (Leonelli, Spichtinger, & Prainsack, 2015), results in creating the entire research process more efficient and transparent (Scheliga & Friesike, 2014). As accessible, open science makes research reachable to all level of inquisitive society (Destro Bisol et al., 2014). Making both research data and opinions readily available online (Grand, Wilkinson, Bultitude, & Winfield, 2016). To share, open science serves as a new avenue of spreading research events (Labastida, 2015). Thus, a guarantee and inherence for research sharing (Munafò et al., 2017). As collaborative develop knowledge, open science facilitate collaboration via web-based tools as well as a fresh tactic research development based on team work and cooperation through network (Ramjoué, 2015).

Data sharing is vital for unremitting scholarly interaction in contemporary research accomplishments. The development of fresh techniques that adjust to embryonic data sharing needs is indispensable (Kitchin & Lauriault, 2015). To produce new knowledge and obtain worthy research, academics in respective of their disciplines need to have access to their counterparts’ research data. Contemporarily, research recently attached more important to data as compare to past (MacMillan, 2014). The concept of data sharing has attracted different meanings by several scholars as it is understood and practiced in a different way by diverse disciplines. Certainly, data sharing practices differ extensively across disciplines in numerous contexts (Kim & Nah, 2018). The study of data sharing among academic is essential, can identify the level of how academics engage in sharing data with others.

Data sharing has been described as the release of research data for use by others, it encompasses actions like ascribing data sets to learned articles, placing data sets in institutional repositories as well as keeping data on an individual computer (Wallis, Rolando, & Borgman, 2013). Data sharing is a situation that makes researchers provide their datasets available to others. It allows verification of results for more transparency and collaboration in academic research Institutions. Data sharing stimulates the transparency of quantitative analytic work, there by offering additional integrity to research results, creating evidence to assist frameworks and decisions, also became a source for researchers to consult when considering how to build upon existing studies (Kim & Adler, 2015). It has a vast potential for research development and will boost academic participations. To achieve this, data produced with public funding should be accessible to all, are critical and form the basis in any meaningful research. For long researchers have learned to share their papers, so it necessary for them to learn how to share their data (Srikanthan, Dwarkadas, & Shen, 2015).

Current technological changes have actualized world access to research data. Technological advancements immensely increased new opportunities by ensuring data integrity via transparency and openness, enhances collecting, storing and analyzing data (Holdren, 2013). Data sharing is regarded as essential for enabling academics to have ease in conducting and promoting research in a way they maximize their potentials. The emergence and growth of such technologies has raised expectations for data sharing therefore, facilitated the collection of several data now than ever before in history thus made global access to research data sets a reality (Pampel et al., 2013). Extensive effort made by academic communities to solve data sharing issues has been identified by previous researches by creating and developing cyberinfrastructure, professional data repositories, metadata, and others tools that can help to promote research data (Kim & Nah, 2018). Despite all these however, there are evidences which shown that data sharing is neither freely available nor commonly practice within the academics as researchers are unwilling to relate this attitude in practice (Mueller-Langer & Andreoli-Versbach, 2018). This dissertation therefore, has the purpose of finding solution to the present gap by exploring ***data sharing practices and the differences in data sharing among academics***

1.1.3 Research Motivation

The yearning to conduct the research data sharing study is appropriate to the demands from different scholars the need for empirical studies in this area. There is the need for comparative studies to deeply understand the term data sharing from diverse angles and also the need for exploratory studies to examine the success of share and reuse data (Naudet et al., 2018). Prior studies revealed that data sharing research is not widely prepared in the academic context (Kim & Stanton, 2012). While prior studies scrutinized researchers' data sharing behaviors by bearing in mind different issues yet, only insufficient studies have investigated academics data sharing in connection to data recycle, that denotes how researchers' prior data reuse experience encourage their data sharing behaviors (Kim & Nah, 2018). The mission and passion to see additional research of this kind made it desirable to conduct this study.

The request by the funding agencies and journal publishers to researchers to ensure openness in research has motivation to conduct a study and grasp more on research data sharing among academics. As part of their policies, researchers and other authors are inspired by journals to offer their data sets of the published articles once requested (Kim & Adler, 2015). The intentions of these agencies, academics and organizations regarding openness and transparency in research highly stimulate the researcher to regulate this study.

This research will be conducted within some public federal universities in Nigeria. This study without doubt supports the interdisciplinary research on data sharing practices. The trend for research is moving towards open science and transparency, therefore, research data sharing has continually been considered a vital instrument for the advancement of knowledge and for preservation and protection against research misconduct. Hence, this thesis has grasp a chance to study on perceptions and practices of research data sharing by academics.

Why the study is on Nigeria? The profusion of research data that exists today has massive potential to solve future advances of research in universities. Data sharing is a prospect that has been discussed by researchers and policy makers for almost three decades (Borgman, 2012). In developed countries, sharing of research data is of increasing interest, with many funders advocating for, or even requiring researchers to share data sets as a condition of funding to maximize their utility and value (Amann et al., 2019; Houtkoop et al., 2018). Even though, between the 2012 International Open Data Conference panels were discussing the first few open data initiatives in developing countries Nigeria inclusive (Majeed, 2012). Sharing activities appear to be unpopular and inconsistent among Nigerian academics (Adeniji, Salau, Awe, & Oludayo, 2018).

Many more reports, conference papers and journal papers looking at open data in developing countries are now available, but they frequently lack conceptual clarity (McGee & Edwards, 2016). It was against this background that in April 2012, the International Development Research Centre (IDRC), the World Wide Web Foundation and the Harvard Berkman Center for Internet and Society invited 30 open data and ICT for development experts from around the world to a workshop in Brasilia to develop a research agenda that would critically examine the impact of open data in developing countries (Perini, Davies & Alonso, 2012). Yet sustained empirical work on open data has been scarce among these nations (Hossain, 2015), this study was initiated to examine the research data sharing practices of academics in one of the developing countries Nigeria.

Previous studies showed there are limited studies on research data sharing in Nigeria (Akintola, 2018). The few studies found only identified a common approach to describing the factors that may account for the success or failure of the open data interventions, without being clear on the nature of open data, its perceptions, the technologies employed, or the intermediaries active, building coherent practical and theoretical understandings of benefits, risks and relevant approaches to open data remains extremely challenging. (Akintola, 2018; Davies & Perini, 2016). Due to a paucity of data sharing research among faculty members in Nigeria universities and the fact that there is no existing framework that provides all constructs needed to data sharing practices among academics, further research needs to be carried out to ascertain Nigerian academics' data sharing practices. This study examined the perception and the influence of organizational, individual and social attributes on data sharing practices of academics in Nigeria. To fill this knowledge gap, research in respect to data sharing in the Nigerian context become necessary.

1.2 Problem Statement

Openness has been labelled as one of the ultimate principles of research and the benefits of research data consist of accountability, transparency, and efficiency. This study aims at addressing the issue of research data sharing perceptions and practices among academics. Current study is apparent significant due to the present lack of in-depth research study on the perception and practices of data sharing especially among academics. Despite a number of funding agencies, academic journals and the kind of support rendering by many researchers towards data sharing practices, "it remains to a large extent an ideal that is rarely implemented" (Andreoli-Versbach & Mueller-Langer, 2014). Data sharing promotes innovation, encourage scientific enquiry, and increase improvement and validation of research method (Dimachki, 2019; Paxton & Tullett, 2019; Wallach, Boyack, & Ioannidis, 2018). It understanding and practices become noteworthy, however, previous studies are being limited in their investigation.

Similarly, data sharing practices vary from one discipline to another, and are mostly been limited to science disciplines (Borgman, 2012). Prior studies revealed that there are limited data sharing practices in the field of in the social sciences (Kim & Stanton, 2012).

In sciences, authors are encouraged to share data by archive primary data sets in a data repository (Kim & Adler, 2015). This prompts for additional empirical studies since the assertion of open data is to let healthier collaboration across academia and other institutions (Groves, 2018). In social sciences, data sharing practices are bound by rules and regulations such as confidentiality, legal and ethical consideration. This difference between social sciences and sciences creates some problems and barriers for data sharing which need immediate attention.

Correspondingly, the above assertions indicated that there is the need for additional empirical studies to explore the perception and practices of data sharing from and around different disciplines. There is undeniable demand for comparative studies to deeply understand the term data sharing from diverse angles and also the need for exploratory studies to examine the awareness and practices of share and reuse data.

Consequently, the present section of the research will highpoint and deliberate the problems that require this study. For straightforwardness in the presentation, these concerns are decided to be presented under the following main captions: (i) Perceptions of academics on data sharing practices, (ii) low participation of academics in data sharing practices (iii) distinction of data sharing practices between diverse disciplines and (iv) lack of suitable platforms for data sharing among academics in Nigeria. The subsequent paragraphs clearly elucidate the points.

1.2.1 Perceptions of academics on data sharing practices

The term data sharing has been viewed differently by diverse researchers from various disciplines and studies. Even though data sharing has the potentials of strengthen the credibility of scholarly publications and can minimize research fraud. It enables open scientific inquiry (Joel, Eastwick, & Finkel, 2018), encourages diversity of analysis and opinions (Naudet et al., 2018), encourages fresh research, simplifies the enlightenment of new scholars (Dowell et al., 2018), permits fresh claims to data not proposed by the original researchers (Doherty et al., 2018), allows the establishment of fresh datasets (Triola, Hawkins, & Skochelak, 2018), and offers a foundation for fresh experiments (Kim & Stanton, 2013).

A number of researchers argued against openness to data and reexamination include potential risk to trial patient confidentiality (Ebrahim et al., 2014); fear of being "scooped and not receiving sufficient credit (Bond – Lamberty, 2018), wrong dredging of data sets, causing in counterfeit conclusions (Doshi, Jefferson, & Del Mar, 2012); and "scoundrel" reanalysis by non- professionals or by analysts who have clash of interest in their final results Brown, Kaiser, and Allison, 2018. Based on the negative perception of data sharing by many researchers, it practice remains to a large extent an ideal that is rarely implemented" (Andreoli-Versbach & Mueller-Langer, 2014). Except for a few researchers that are from disciplines that embraced data sharing such as genomics, many scholars from other fields attached negative views to data sharing and are not ready to share data with other researchers (Dreyfus & Sobel, 2018; Elliott, Cheruvelil, Montgomery, & Soranno, 2016; Madas & Schofield, 2018; Mueller-Langer & Andreoli-Versbach, 2018; Ross, Iguchi, & Panicker, 2018).

1.2.2 Participation of academics in data sharing practices

Data sharing can potentially provide a lot of benefits; it is an essential feature for research credibility which simplifies the progress of subsequent research. Literatures revealed researchers hardly involve in data sharing practices. Researchers seems to recognize the importance of data sharing yet, are reluctant to apply this principle in practices (Mueller-Langer & Watt, 2014). Researchers consider costs of releasing data appear to be greater than their benefits connected with data sharing, which results to an equilibrium with minimal sharing (Mueller-Langer & Andreoli-Versbach, 2018). Likewise, increase effort, time and energy experiencing in data sharing also deject researchers' participation either direct and indirectly. Other scholars also identified effort expectancy influence humans' attitudes concerning certain behavior include data sharing (Kim & Stanton, 2016).

Furthermore, quite a number of researches have equally identified perceived risks involved in data sharing to be one of the reasons why some researchers never participate in sharing data with others. Researchers become worrying when they view sharing data may lead to misuse and criticism by peers. These risks potentially have a negative impact on researchers' career (Kim, Lee, & Elias, 2015). Misuse of data often affect data sharing practices among the academics, as many researchers were concern that making unanalyzed data accessible could result to inappropriate use of the data or incorrect interpretation (Bezuidenhout, 2013). Data sharing preparation required a lot of time and effort which become a factor preventing researchers participating from data sharing (Kim & Adler, 2015). Data sharing in most cases are proven to be difficult; the competition for reputation among academics can be a barrier within the researchers to share their data. The idea of who owned the data and where the data is situated is also a barrier in data sharing, it can be nontrivial problem. Researchers consider datasets as intellectual property thus, do not want others to benefit from it. The idea of extra monopolistic from these data makes data sharing not to be a common practice among the academic communities. Many academic scholars find it difficult to share their dataset publicly as a result perceived individual cost which include time, money reputation and chance of being scooped by fellows regarding future publications (Pitt & Tang, 2013). Sharing of data is not easy for example while scientists believe in maintaining exclusive control over their data, the economists look at data as a source of 'monopoly rents'. Sometimes certain data may have confidentiality restrictions that disallow them from being shared (Abowd, Schmutte, & Vilhuber, 2018).

1.2.3 Disparity in data sharing practices among disciplines

Regardless of discipline, research data should be shared beyond its primary purpose for which they are created. Every discipline's practice of sharing varies in relation to the capacity of data created, alleged importance of sharing and moral restrictions. Sciences have well established culture and experiences of sharing research data with their colleagues (Kim & Stanton, 2013). In fact, majorityof researches on data sharing largely deals with the sciences depriving or given less emphasis on the social sciences (Kim & Adler, 2015).

While the important of data sharing have been well documented within several academic fields, the actualization and promises solidly rest on the respective discipline. Research data sharingvaries from discipline to discipline, their capabilities and practices differ. The reason is not far away from differences in value chain of data, publications and other related objects are not in the same rate rather it differs among disciplines (Shen, 2018). Every discipline has different methods in practicing its data sharing. Data sharing practices differ from each discipline in terms of the number and value of data to share and produce. For example, while data in some discipline grows faster in some disciplines because of the technical or even financial capabilities seems to be sluggish.

While in life science data sharing is encouraged researchers in arts and humanity mostly considered works in monographs. In social science there are certain guidelines regarding data sharing that are bound by rules relating to confidentiality and legal or ethical consideration. Thus, data sharing is particularly tough for social scientists since data are dispersed between countless sources and programs (Kim, Yoon, & Zo, 2015). Another study conducted showed researchers in the sciences welcome sharing practices as compare to their colleagues in the social sciences where human subjects and other constraints may originate and affect datasets (Zenk-Möltgen & Lepthien, 2014). Despite the increase consciousness of the important of shared data, absent of suitable guidelines and principles across some fields of studies made sharing become uncommon practice among their researchers (Kim & Adler, 2015). Generally, researchers in respective of their fields own diverse approaches and beliefs for handling and sharing research data (Hall, 2013). These disparities among has negatively affected the growth and development of data sharing in academic context.

From the aforementioned, in keeping with the new threat in research on data sharing, recent available literature calls for empirical studies to examine and determine the various practices, culture and methodologies to enhance data sharing strategies within the university and other research institutions (Haeussler, 2011).

1.2.4 Lack of suitable platforms for data sharing among academics in Nigeria

In Nigeria, the history of resource sharing started in 1963 at the "National Library of Nigeria" (Abubakar, Musa, Ahmed, & Hussaini, 2007). The literature analysed has not indicated any serious practices of data sharing among academics in Nigeria. This lack has often been linked to lack of platform for effective practices (Ogba, 2014). Inadequate fund to acquire digital paraphernalia was understood to be a restriction to resource sharing in Nigeria (Komolafe-Opadeji, 2011). Even though some universities have information communication Technology (ICT) equipment yet were found not practicing resource sharing (Adam & Usman, 2013). Findings further showed that academics who are in a better position to participate in sharing lack ICT skills (Abubakar et al., 2007). While some literatures have shown that Nigerian academics are aware of resource sharing and the its benefits but do not always practice it (Ogba, 2014).

There is also deficient in the literature of any study on data sharing among academics in Nigeria as the literature reviewed focused on resource sharing in Nigerian universities. The present study intents to explore the research data collaboration and the differences that occur between Nigerian academics in data sharing. This becomes a big gap which this study would fill by exploring data sharing among academics in Nigeria.

1.3 Research Objectives

The following are the objectives of this study

1. To examine the perceptions of research data sharing among academics.
2. To investigate the factors that influence academics' data sharing practices.

1.4 Research questions

The following are the research questions related to the mentioned research aims.

1. How does Nigerian academic community perceive data sharing?
2. What are the motivations of research data sharing to academics?
3. What are the perceived risks for academics in sharing their research data?
4. What are the personal attributes that influence academics' data sharing practices?
5. What are the organisational attributes that influence academics' data sharing practices?
6. What are the social attributes that influence academics' data sharing practices?
7. What are the differences in data sharing practices between social sciences and sciences?

1.5 Significance of the study

Recently, data sharing has become an interested field of research for scholars to collaborate and interact with each other. Data sharing has been defined as the ability to share the same data with multiple researchers (Andreoli-Versbach & Mueller-Langer, 2014). Generally, academics from different disciplines need to share data with others. In recent time, there has been more attention to research data sharing (Kindling, Fütterer, Sandt, & Petrus, 2014). Having seen the acknowledgement supported by literature for making data freely available to scholars, it is not out of point to say that the ability to access data is critically to the advancement of research in university communities. Within the academic context, this research contributes immensely to the enhancement of data sharing culture, understanding and promoting of data sharing practices, encouraged scholars' collaboration and refining a data sharing framework across all disciplines in universities.

Similarly, this study provides scholars even among the developing countries, with the opportunities to be better connected and share data within them. Research on data sharing benefits researchers as it makes them to have idea of their peers' original research areas (Pitt & Tang, 2013). With good data sharing practices, there would be new collaborations and scholars' reputations could increase.

The extant data sharing literature reveals that an overabundance of studies have concentrated and only interested in technical aspects of data sharing such as having adequate data sharing infrastructure and neglected the users' perception towards data sharing or even reuse data from the databases (Janssen, Charalabidis, & Zuiderwijk, 2012). Based on data sharing literature, investigation on the perceptions of data sharing among academic members is considered a vital contribution.

The study will be a source and basis for future researches that focus on how academics gather and share their data with the hope to achieve the universities goals and objectives. Again, the literature analysis also showed that there are a lot of arguments among the scholars on the need for additional empirical studies to explore and determine data sharing from and around different disciplines. Therefore, this study will be a benefit to those from the department of library and information sciences as it serves as an additional literature.

Despite the importance of data sharing within the academic environment, very little is achieved in this regard. Existing research on data sharing are inadequate in explaining the characteristics and behaviors of researchers concerning data sharing. Prior studies revealed that exploring the position of data sharing status within a discipline was challenging due to the dearth of data therefore not prepared (Dai et al., 2018). Suggestions provided in this study will aid various scholars in with similar problems on research data sharing among academicians.

So, current research inspired to offer an inclusive consciousness of data sharing perceptions and also examine the factors influencing data sharing within academic communities using theory of organizational culture.

1.6 Limitations of the study

Present study plans to cover federal universities in the Northeast Nigeria and might not cover the states own Universities. The study might not equally investigate the various types of data to be shared. The data collected are restricted to only lecturers within the universities covered for this study. This study was conducted only at the public universities as a result, findings may not be generalized to a related research that involves private Universities.

1.7 Organization of Thesis

This thesis is organized in six different chapters and every chapter commenced with an introduction and finishes with a particular summary. The following paragraphs are the miniature enlightenments of the respectively chapters.

The opening chapter, which is chapter 1 comprises of the introduction, overview, background of the study, research motivation, problem statement, research objectives, research questions, significance of the study, limitations of the study, and organization of thesis are also presented in this chapter. Indication from prior studies specify that academics have a major role in the achievement of research data sharing practices, therefore, understanding the perceptions and practices of research data sharing practices among academics is significant.

Chapter 2 offers an assessment of related literature that comprises; Overview of the chapter, open science and data sharing, scholarly communication, perceptions on research data sharing, data sharing and data withholding, issues in data sharing, data sharing practices between social sciences and sciences scholars, the research gaps, related theories and theory of organizational culture and lastly summary.

Chapter 3 presents the overview, research design, theoretical framework, justification of using organizational culture, interview with interview guides, population and sample techniques, preliminary study, data collection, validity and reliability, ethics, data analysis. Then survey, research framework, variables and hypotheses development, instrument development, population and sample techniques, administration of the study, consent letter, data analysis, pilot study and summary.

Chapter 4 offers overview, participants' demographics, results of RQ1, RQ2 and RQ3, usefulness of interview to the development of the survey instrument and lastly summary.

Chapter 5 commences with the introduction, data preparation, data editing and cleaning, response rate, descriptive statistics, descriptive analysis of the measurement scale, statistical testing of measurement methods, measurement model assessment (outer model), assessing structural assessment (inner model), PLS path modelling algorithm, answering survey research questions and summary.

Chapter 6 starts with introduction, concluding remarks, constructs based on the theory of organizational culture, challenges during data collection, research contributions, limitations of the study, future research and recommendations and conclusion.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

In current chapter, previous research knowledge together with their findings and scholarly papers are wholly consulted. These related literatures are reviewed with the aim to reveal research gaps for the direction of this research. The key objective of this chapter is to create the consciousness of research data sharing perspectives and practices among Nigeria academics. There is presentation of relevant literature which explains and justifies the intent of this study. This chapter mainly divided into 2; empirical and literature and theoretical literature and is alienated into nine key sections. Earliest section brings an overview of the entire chapter, section two explains the concepts of open science and data sharing, next section three examines the perceptions of data sharing within the academics. Section four and five elaborate the concepts of scholarly communication and data sharing/withholding respectively. These sections are used as the building blocks to help understanding the current stand of research data sharing in academic context. Section six deliberates about issues that impact research data sharing. This section defines and conceptualize factors influence data sharing. Section seven presents the literature analysis conducted on previous work-related disparity of research data sharing practices between social sciences and sciences scholars. The next section which is section eight gives limitations or the research gap of the previous study and finally, the last section, section nine is the summary. Research model is presented to help in clarifying the complete research flow.

2.2 Open Science and Data Sharing

A spirit of openness is getting attraction in the academic community, and is the only way meant to address a 'crisis' in research in an academic environment (Gewin, 2016). Data sharing in open science is an effort raising stable impetus: a request to make research data, software code and other research techniques publicly available and transparent.

Open science can be seen as a process where people collaborate and contribute, a situation that research data and other research processes are freely available to enable reuse, redistribution and reproduction of the research (Mons et al., 2017). Open science refers to conducting research in a collaborative manner by sharing and reusing research data and relevant materials (Foster & Deardorff, 2017). It is all about spreading the principles of openness to entire research cycle, developing sharing and collaboration as early as possible (Kiernan, 2016). Open science comprises all activities targeting to eliminate the walls to sharing any type of output, resources, methods, or tools at any stage of the research process. To facilitate openness at diverse phases of research process (Miguel et al., 2014). An important symbol of researchers is the transparency and reproducibility of their research results. Lack of transparency is therefore a blow to research development. There is some proof that articles with open access gain more citations, especially when related data is also published openly (Toelch & Ostwald, 2018). Funding agencies and policy makers have acquainted with some stringent principles for how research data should be freely accessible. These new requests, which originate as a result of 'open science that have a direct influence, more especially to the early researchers: there is need for the young researchers to give guarantee that their research practices are in accordance with the established requirements for their work to be published or apply for funding (Lilienfeld, 2017). Open science is an effort aiming to remove the barriers for sharing any kind of data and other research output at any stage of the research process. For that, open research data, open access to publications and general open collaboration are all under the umbrella of Open science (Denzin & Giardina, 2018). The motive behind open science is difficult however, one key opinion is any kind of data that everybody should have access to without cost.

Similarly, open science signifies a fresh method to the research practice based on collaborative work and unique means of spreading information by means of digital technologies and new cooperative tools (Kirkeboen, Leuven, & Mogstad, 2016). A demand to make research data openly accessible and transparent. Open science practices can be of benefit to researchers especially early researchers by intensifying their visibility and increasing their network. Besides, researchers would also benefit from the availability of research data and code in their own research projects (Toelch & Ostwald, 2018). Open science emerged as a significant concept in academic research, it provides open innovation which lead to three opens (Open Innovation, Open Science, and Open to the World) that has discussed at length (Bogers, Chesbrough, & Moedas, 2018).

In the area of advance research and practice, there is often a trend for funding agencies to drive for extra openness by means of technological research interferences, often for the sake of technology itself (Bezuidenhout, Kelly, Leonelli, & Rappert, 2017). An "open science effort" is getting grip across many disciplines within the research environment as well as hastening dismay among those who concern that too much disturbance may be hindering professional production. In spite of this disturbance, advocates of open data collaboration have maintained that some of the major difficulties of the 21st century must be resolved with the help of many people and that data sharing will be the essential train to make that happen. In the United States for example, a national strategic plan for data sharing encouraged the federally funded scientific agencies to (a) publish open data for community use in discoverable, machine-readable, and useful ways; (b) work with public and civil society organizations to set priorities for data to be shared; (c) support innovation and feedback on open data solutions; and (d) continue efforts to release and enhance high-priority data sets funded by taxpayer dollars (Hesse, 2018).

2.3 Scholarly Communication

The concept of scholarly communication connotes the progression by which academics or researchers share and circulate their research findings for others in the academic circle and beyond to get it freely available. Nevertheless, scholarly communication is a very complex ecosystem encompassing several diverse players, among which are publishers, librarians, faculty members, funding agencies, and the host of others (Wipperman, Martin, & Bowley, 2018). Contemporarily, every discipline has its own open access journals with Open access indexing services are also available (Willinsky, 2018). Scholarly communication are mainly scholarly writings preserved for use and reuse by future generations. Modern day technology has given rise to a number of changes on how scholarly research is conducted and communicated with researchers are increasingly projected to accomplish and share research data (Hall, 2013). The forecasts of open access publishing for research has enthused the creation of a Public Library of Science, which originally gabbed for a stay away from any of non‐ open access journals (Willinsky, 2018).

In order to have unique research data practices, better understanding of scholar's comportments concerning research data is necessary. Study conducted by Scaramozzino, Ramirez, and Mc Gauges sightsees academics' data sharing behaviors and discovers that virtually all researchers agree that counterparts should share their data, but in reality very few actually share with scholars outside their research group (Scaramozzino, Ramírez, & McGaughey, 2012). Any researcher that hesitate to share research data has reasons for doing so with many overlapping and at times inconsistent views about making free international access to research data (Tenopir et al., 2011). Majority of the researchers see value in sharing researcher data and those that are not interested in sharing felt that their data was trivial to be valuable in a diverse study and also consider the aggregate of effort required to organize the data to make it useful to someone else (Hall, 2013).

Information and communication technologies (ICTs) had recently been developed with great influence on academic's communication capacity. The information landscapes within which scholars work is undergoing a seismic shift. The computer monitor that rises out of the photocopy stacks, piles of journals, clippings and correspondence, now offers a new, rich vein of information that seems destined to eventually overwhelm the traditional trappings of desktops, filing cabinets, and bookshelves (Willinsky, 2018). This has introduced new facilities that transformed outmoded manner of sharing research data such as academic blog, online conference, open access service e-journal and even virtual forum have emerged which provide scholars with an extensive and variety of options in retrieving, publicize and contribute their data.

The quick advancement in the area of computerization offers academics the chance to work in partnership and sharing data with colleagues through computer-generated outfits which made researchers to involve in using online scholar communication services (Zhao, Hao, Zhao, & Han, 2010). The term virtual scholarly communication originates in 1960s to connote transfer of information via computer (Berge & Collins, 1995). For the benefit of this research, online scholarly has been described as events by involve using computer network. However, the ambition of old-fashioned scholarly communication remains unchanged, but then by diverse communication media. Is therefore, left for the researchers to copiously take advantage of virtual services to enhance and transform present scholarly communication system.

Researchers in the modern days' use more of internet and other online means to share data and this change causes modification of scholarly communication system as the internet turns to a significant way for research data sharing among scholars (Wilkinson, Harries, Thelwall, & Price, 2003). In several occasions, evidences show that online scholarly communication service assimilate and support numerous tasks that include sharing, retrieval and discussion forum, yet concerns regarding resources management, funding and maintenance remained unsolved (Lai, 2010). Having realized the change of scholarly communication is gradually happening, open access and data sharing have gotten excessive care from various investigators hoping to encourage strategy and move towards restructuring scholarly communication system to provide various sharing through information and communication technologies, and to form justifiable scholarly communication system which might meet the prerequisite of the researchers.

2.4 Perceptions on Research Data Sharing

Research data sharing is important, it denotes the range to which academics offer their data to other investigators through placing data sets in institutional data repositories (Kim & Nah, 2018). Data sharing is also defined as "the release of research data for use by others" (Borgman, 2012). While other study labels data sharing as "encompassing activities such as attaching data sets to scholarly articles, depositing data sets in repositories, or saving data on a personal computer or local server" (Wallis et al., 2013). Data sharing is seen as sharing data between colleagues and system in ways that preserve the meaning and integrity of the data (Lyon, 2016). Sharing data also increase the economic development. It is perceived as valuable sources for economic growth (Hina, Selvam, & Lowry, 2019). Research data sharing is regarded as essential for enabling academics to have ease in conducting and promoting research in a way they maximize their potentials. It can be seen as a researcher's activities to provide raw data of his or her published work to other researchers freely. Also serves as a key for any empirical study, is the basis of research in several disciplines, it plays a central role of facilitating and improving research in academic communities. In recent time, there has been more attention to data sharing in researches (Kindling et al., 2014). Thus, research data sharing is widely acknowledged however, in actual sense, it practices is rather limited among academics (Linek, Fecher, Friesike, & Hebing, 2017). And that scholars do not frequently make their research data especially electronic version freely available to other investigators due to insufficient time and lack of funding (Linek et al., 2017). Despite it's potential to hasten progress in research, public data sharing remains relatively uncommon (Houtkoop et al., 2018). Researchers asserted that risks linked with sharing data with someone they did not choose to share data with make them withhold their data (Meyer, 2018).

Researchers perceive data sharing differently with majority felt data sharing is a blessing to academics' environment and few regard it to be of no value. While data sharing is that situation that allows data used for scholarly research freely to others researchers, the term data withholding denotes declining to offer data to other investigators (Tenopir et al., 2015). With the advent of information technology, researchers have considered data sharing an inevitable issue (Lyon, 2016). Technological advancements immensely increased new opportunities by ensuring data integrity via transparency and openness, enhances collecting, storing and analyzing data (Holdren, 2013). For quite a few decades, researchers have realized the importance of research data sharing. Research data sharing has continually been considered a vital instrument for the advancement of knowledge and for preservation and protection against research misconduct. Broadly speaking, research data sharing is seen as the fundamental mechanism for transparency" (Taylor & Kelsey, 2016). However, based on how some researcher view the concept of data sharing, it is not practically encouraged and cherished by some of the researchers across many disciplines (Zenk-Möltgen et al., 2018).

With research data sharing practices, scholars could be able to access the work of their colleagues. Data sharing increases the transparency of quantitative analytic work, there by lending more credibility to research findings, providing evidence to support frameworks and decisions, and a source for researchers to consult when considering how to build upon existing studies (Kim & Adler, 2015). The practice of research data sharing has grown significantly with pressure being placed on researchers and authors across all disciplines in academic communities to make their raw data more open and accessible. It was observed that papers were often cited more with open data compare with those without the data available (Piwowar & Vision, 2013). Currently, different government and agencies put more effort in introducing and enforcing open access and data sharing policies. The aptitude to merge data across datasets, catalogs, domains, and cultures can offer data handlers with the talent to discover, access, assimilate, and analyze combinations of datasets based on their desires (Hendler, 2014). That is why today, there is a lot of emphasize about data sharing and reuse among scholars in respective of their discipline. “The front-runners of the academic community are readjusting their requests, asserting for the sharing of data and better experimental transparency (Achenbach, 2015). It became significant to appreciate that even though to share is good and considered a perfect idea yet, there are evidences that researchers withhold their data and are afraid their data will be used in ways they do not intent to and thus perceived a real concern (Wallis et al., 2013). The reality is not all research data can be provided to every researcher as some may contain personal information and has a potential risk of exposing the privacy of the respondent in several ways (Hina et al., 2019). Similarly, misuse of data often affect data sharing among the academics, as many researchers were concern that making unanalyzed data accessible could result to inappropriate use of the data or incorrect interpretation (Bezuidenhout, 2013).

The reuse of open research data is heralded as having the potential to increase effectiveness, productivity, and reproducibility in research (Wilkinson et al., 2016). However, based on the way other researchers perceived it, data do not flow easily between users, situations, and disciplines (Borgman, 2015). As academic communities are experiencing a changing to more data-driven methodologies, the study of research data is necessary to identify the actual data practices and service requirement. In 2014, the Public Library of Science (PLOS) journals made a policy that can force the various authors to provide data from their published manuscript freely available to others (Bloom, Ganley, & Winker, 2014). Also, quite a number of funding agencies or institutions, and other journal publishers require authors from all disciplines to share their data. These agencies and journals have policies regarding data sharing with the belief of having transparency and openness in research.

In Nigeria, perception of sharing data among scholars differs based on their disciplines. Thus, every field has different ways of dealing with data sharing (Kratz & Strasser, 2015). For example, the perceptions of those from the medicines who mostly deal with human beings may differ from those in the social sciences that deal with journal data-sharing policies (Bertagnolli et al., 2017). Therefore, data sharing practices of each researcher depend on the way they perceive and attach value to sharing. Kim (2013) found that the policies and plans used by scholars for data sharing practices differ from one discipline to another.

2.5 Data Sharing and Data Withholding

Materials consulted cover both data sharing and data withholding, data sharing has recently gained relevancies in academic communities driven by an aspiration to accrue reputation (Linek et al., 2017). The needs for data sharing has been recently more emphasized around the scholarly world. While data sharing is that situation that allows data used for scholarly research freely to others researchers, the term data withholding denotes declining to make available data to other investigators when are anticipated to offer their data by various methods. Long before now, researchers have been busy sharing their papers, presently they need to capitalize on sharing their data (Shen, 2016).

Currently, different government and other agencies put more effort in introducing and enforcing open access and data sharing policies. (Hendler, 2014), observed that, the aptitude to merge data across datasets, catalogs, domains, and cultures can offer data handlers with the talent to discover, access, assimilate, and analyze combinations of datasets based on their desires. That is why today, there is a lot of emphasize about data sharing and reuse among scholars in respective of their discipline. “The front-runners of the academic community are readjusting their requests, asserting for the sharing of data and better experimental transparency (Achenbach, 2015).

Even though to share is good and considered a perfect idea yet, there are evidences that researchers withhold their data and are afraid their data will be used in ways they do not intent to and thus perceived a real concern (Reichman, Jones, & Schildhauer, 2011). The reality is not all research data can be provided to every researcher as some may contain personal information and has a potential risk of exposing the privacy of the respondent in several ways (Hina et al., 2019). Other researchers withhold their data because they believe that it takes time and efforts to prepare data for publication hence, feel that they have already shared their data when an article is published.

Recent studies regarding data sharing and withholding gave more consideration on the context of data sharing and withholding, its benefits and barriers, capitalized on pervasiveness of data sharing and withholding and other impacts of data sharing and withholding (Borgman, 2012; Kim and Stanton, 2013; Pitt and Tang, 2013; Shen, 2016). While data sharing has been well embraced by the academic communities with the notion that may enhance the quality of research, the reality is majority of the researchers are still reluctant to share rather prepare to withhold their data (Piwowar, 2011; Tenopir et al., 2011). To encourage more participation in data sharing practices, (Faniel & Yakel, 2011). developed a well-coordinated research agenda aim to investigate researchers' data practices from all disciplines in academic communities.

Sharing and withholding of research data is a topic of intense discussion among academic community. Although a lot of researchers studied the prevalence of data sharing and withholding, few were able to address this issue (Campbell, Weissman, Causino, & Blumenthal, 2000). Several investigations reveal that openness to research data has a huge benefit for research development, it simplifies the replication of study results and permits the application of old data in new environments (Fecher, Friesike, and Hebing, 2015). That is why the idea of research data sharing got a unanimous support among academic stakeholders. A precise example can be seen from the European Commission that announces that contact to such data will improve Europe's innovation capacity, to achieve this potential, data generated with EU funding should be accessible from 2014 onwards (Bonini, Eichler, Wathion, & Rasi, 2014).

By contrast, a number of such research argued against openness to data and reexamination include potential risk to trial patient confidentiality (Ebrahim et al., 2014) wrong dredging of data sets, causing in counterfeit conclusions (Doshi et al., 2012); the requirement for a data infrastructure for sharing data and reanalysis (Berman & Cerf, 2013); and "scoundrel" reanalysis by non- professionals or by analysts who have clash of interest in their final results, for example, the Methane Awareness Resource Group Diesel Coalition which tried to frustrate a study presenting association of diesel exhaust with cancer outcomes via multiple requests for raw data for reanalysis (Monforton, 2006).

Data sharing practice is imperative, a comprehensive study conducted by Publishing Research Consortium (PRC) in 2010 with 3823 respondents, divulge that access to datasets, data plans, procedures and data reproductions was rated important or highly important; conversely, only 38% of them fingered that they were simply available (Tenopir et al., 2011). Numerous earlier surveys have discovered the benefits and barriers of sharing data and the level to which researchers share or withhold data (Vickers, 2011). Results appear to recommend that current sharing practices are negligible, while the amount of data sharing differs between diverse disciplines. Some journals have particular guiding principles which require scholars to share their data with other researchers. However, the degree to which these rules are supported remains largely unproven. Savage and Vickers demanded data from ten investigators who had published articles in PLoS journals, which have particular data sharing policies. Only one scholar offered an original dataset (Savage & Vickers, 2009).

The level of data withholding normally be determined by the publication status of research. From different disciplines, studies revealed how researchers withhold their data. For instance, in science, the research in the field of genetic by Louis, Jones, and Campbell, (2002) discovered about 30% of genetic scientists testified withholding and or lack of making data available before publication is done, some few years. Similarly, (Piwowar, 2011) piloted one more research which used bibliometric analysis to find how often raw gene expression microarray datasets were shared after publication. To her greatest surprise, she realized only but 25% out of the total of 11,603 articles on gene expression microarray issued between 2000 and 2009 delivered their rare datasets in main data repositories. Again, Reidpath and Allotey, (2001) demanded author's publication-related data of 29 articles available in the British Medical Journal, but only single author gave out the demanded data.

In the field of social sciences, the Emory University Libraries in Atlanta, Georgia in 2012 embarked on a study with 330 researchers from the university faculty (Akers & Doty, 2013)'. Research results discovered some motives behind researchers' data withholding to include; nature and the kind of the data (sensitive or personal); recognition of the researcher; and misuse and misinterpretation of data. Equally, Savage and Vickers undertook a related study in 2009 that shown some investigators decided to withhold as a result of the effort involved in making such data available (Savage and Vickers, 2009). In respect to the field of psychology, some scholars like Wicherts, Borsboom, Kats, and Molenaar, (2006) demanded research data from 141 investigators and or authors of articles that were issued in American Psychological Association (APA) journals discovered that 38, which constituted merely 27.0%, of those investigators made theirs available despite the request made.

The above studies have clearly show the prevalence of data sharing as while as withholding in academic communities, and varies from one field to another. Despite the technological advancement, there are researches that vividly indicted the non-readiness of scholars to share data with others (Borgman, 2012; Tenopir et al., 2011).

2.6 Issues in Data Sharing

With the advent of social networks, the modern research has considered data sharing an inevitable issue. Because social networks have changed completely the process discovering which more or less turned to data centered research. Hence, data sharing presently became vital within contemporary research undertakings. Data sharing is a paramount issue between modern researchers especially now that the world has been made to be a small area through social media with e-science transformed the procedure of research by facilitating researchers' participation in data sharing via online collaborative determination (Kim and Stanton, 2013). The following can be identified in this research as some of the factors that influence research data sharing practices; Funding agencies, journal publishers, perceived effort, anticipated rewards, Risks and altruism and the present of data repository.

2.6.1 Data Repository

This concept can be described as an initiative aims at storing data for an analytical or reporting purpose. Presently, having recognized the significant and the relevancies of the term data sharing, academic communities have established different data repositories to realize their dreams (Gewin, 2016; Tenopir et al., 2015). Current development in the area of technologies brought about data repositories that enabled researchers to share their research data with their research publications without difficulty, thus achieving the main objective of modern research which is data driven on shared data sets (Kim, 2017). Currently, collaboration in form of data sharing in academics desperately needs the composition of institutional support like providing data repositories, technological set-up and even interpersonal relations (Kim and Stanton, 2012). Correspondingly, a successful academic's data sharing must encompass the similar three ranges of infrastructure, institutions and people. If we really consider data sharing practices as significant and an evolving tributary in research, creating data repositories becomes critical to modern academic communities.

It is equally important to know that research data sharing transpires in miscellaneous forms, including uploading data in data repositories, succumbing data as journal supplements and providing data by means of personal communication methods upon demand (Kim, 2017). By implication, Universities communities with more data repositories may involve in sharing practices more than those with less. Equally, even in similar communities, data sharing practices can vary based on the present of data repositories. In science, there is no doubt that the volume of data being assembled is speedily increasing more especially in biomedical research laboratories, physics experiments and genomics which necessitated the need for data repositories (Farber, 2017).

Establishing data repositories in our Universities can really help and influence data sharing activities of our scholars. A latest viewpoint (Stephens, 2015) claims that the quantity of sequencing data created is amplifying every seven months and it has been assessed that the unit cost of storage capacity declines haphazardly, this is coarsely dependable with the development of data appears to be cumulating by an order of magnitude roughly every 31 months since January 2009 (Kodama, Shumway, & Leinonen, 2011). Data repositories over the years is influencing and changing data sharing practices in the academic environment by permitting researchers to deposit their raw data as well as making such data mostly available to everybody who might want to use them.

2.6.2 Funding Agencies

It is widely believed that funding or government agencies are of the view that data generated should be shared within the various researchers. These agencies normally pressurized researchers about their data sharing behaviors to make sure that researchers collaborate. These agencies sometimes do create data management and sharing policies that can encourage sharing raw data with others. There should be a data deluge to have enough data for use by anyone, anywhere and anytime (Baraniuk, 2011). If this is being realized, then researchers that provide data must share them accordantly (Borgman, 2012). Even though, sharing research data is considering an intricate and very difficult problem. Despite pressure from the funding agencies, not much sharing may be taking place and appear to happen in a few disciplines with inconsistency (Wynholds, Fearon Jr, Borgman, & Traweek, 2011). When it became a plan by data management to impose data sharing among scholars through funding agencies, the researchers without hesitation revolved to research-supporting staff such as grant officers, service providers, information scientists, librarians and the host of others in order to address the requirements (Li & Tschirhart, 2012).

Research funders were often requiring data release with some incentives. For example, the National Institutes of Health (NIH) provided a data management plan requirement in 2003 for grants over $500,000 (Gold, Rimal, Nolan, & Nelson, 2007). National Science Foundation also required data sharing in its grant contracts to encourage sharing among researchers (Alter & Gonzalez, 2018). No matter the case may be, researchers are expected to share their data with other researchers without delay as they are usually being giving grants and such grantees are expected to encourage and facilitate such sharing practices. National Science Foundation 2010 has also made it clear that all future grant proposals would need at least two-page data management plan that would take care of the above-mentioned requirement (Kopko, Edwards, Krause, & McGonigle, 2016).

Similarly, U.K research funders also established data release policies to encourage sharing of data in the 1990s. This led to the Digital Curation Centre (DCC) created several templates for data management plans corresponding to the requirements of individual U.K funding agencies (Abbott, 2015). All these resource dominant organizations (funding agencies) that increase regulative pressures on researchers can decide to control the funding allocated to them which can make the researchers to easily comply.

2.6.3 Journal Publishers

The pressure to share data by authors to journal publishers is enormous, authors can share their research data in a variety of ways. Journal publishers always want researchers to share data with the hope to have more funding or publish articles in their journals. Journals normally necessitate and encourage writers to make data freely available. Related to pressures by funding agencies, journal publishers do place regulative pressures on the authors via editorial policies on data sharing. As part of their policies, both science and social science authors are encouraging by journals to provide their data sets of the published articles upon request (Kim and Adler, 2015).

Previous studies have shown that pressures from Journal publishers have influenced researchers' behaviors towards sharing data (Taichman et al., 2016). Therefore, these journal publishers serve as a window for disseminating and evaluating research data (Munafò et al., 2017). Despite the fact that not all disciplines are well practicing data sharing as a common research practice, a considerable number of journal have applied data sharing policies (Tenopir et al., 2011; Tenopir et al., 2015).

2.6.4 Anticipated Rewards

Series of studies cogitated anticipated reward as one of the factors affecting research data sharing. This is a process where the researcher feels that data sharing could provide rewards like reputation and recognition. This has been observed by many scholars, professional recognition (Ellaway, Pusic, Galbraith, & Cameron, 2014), institutional recognition (Tenopir et al., 2015) and academic reward (Kim, 2017). These have impact on research data sharing. Rewards can be realized through citations or even acknowledgements and sometime authorship (Rowhani-Farid, Allen, & Barnett, 2017).

Researchers view data sharing as given that prospects for academic reimbursements by way of citation and or authorship that can develop their academic career (Kim and Adler, 2015). Studies have shown that expected rewards of any kind in organizations affect positively the attitudes and intention to share data or knowledge. Whenever there is low or sometime no rewards, researchers are unlikely to share their data with colleagues. The ability to periodically get commendations via email or social networks on the data shared by researchers also influence positively the attitudes of such researchers regarding their data sharing behaviors (Ziefle, Halbey, & Kowalewski, 2016).

2.6.5 Risks

This has to do with the potential uncertain and negative outcomes in the process of sharing data. Researchers consider data sharing as risk that can involve losing publication, misuse and misinterpretation as while as criticism by their peers, which may negatively influence researchers' data sharing practices. Data sharing become risky and put doubt in the mind of the researchers. Therefore, affects scholars' career undesirably. In social science for example, researchers become worrying when they view sharing data may lead to misuse and criticism by peers. These risks potentially may have negative impact on researchers' career (Kim, Lee, and Elias, 2015). A number of researches have equally identified perceived risks involved in data sharing to be one of the reasons why some researchers stay away from sharing their data with others (Tenopir et al., 2011). While the ability to share and access data is vigorous to the growth of research, scholars are always conscious of the legitimate concern involved in the data sharing process. Researchers have not forgotten the implications that the threat involved have for their lives.

Similarly, other legitimate concern involved in data sharing is privacy control as several investigators have indicated that privacy is another important factor that influences how researchers go about sharing their data. The frequent finding of flaws in data anonymization and of course the issue of data mining resulted to ethical and privacy concerns in data sharing (Corti, Van den Eynden, Bishop, & Woollard, 2019). These concerns are applying more by some researchers than others, for instance, those from the clinical or medical are more concerned about protecting their data. To share is good and considered a perfect idea yet, people are afraid their data will be used in ways they do not intent to and thus perceived a real privacy concern (Eastin, Brinson, Doorey, & Wilcox, 2016). Privacy and data privacy regulation play a large role in deciding whether data should be shared or not, some ethical issues like concerns about privacy and confidentiality, concerns about moral distance, and the possibility of valid consent also influenced research data sharing negatively (Yang, Li, & Niu, 2015).

2.7 Data Sharing Practices Between Social Sciences and Science Scholars

Research data are significant productivity of the scholarly research, regardless of which discipline or field of study, in recent time, data sharing has been a hot topic as attention to issues of data sharing are fully given in the academic community (Bond–Lamberty, 2018; Zenk-Möltgen et al., 2018). Quite a good number of researches and papers recently investigated data sharing practices among different faculties particularly among sciences and social sciences. The findings for these researches indicate scientists share data more than the social scientists. These researches and papers include some of the following; (Borgman & Pasquetto, 2018; Cooper, 2018; Iqbal, Wallach, Khoury, Schully, & Ioannidis, 2016; Kim & Adler, 2015; Kim & Stanton, 2016; Masa'deh, Obeidat, & Tarhini, 2016; Vitak, Shilton, & Ashktorab, 2016). They have offered extensively the various attitudes and behaviors of researchers in relation to data and sharing in diverse fields. These studies revealed wide disparities in the philosophy and practices of data sharing among disciplines which showed every respective academic field has different approaches use and charge in their data-sharing practices (Kim and Stanton, 2013).

Ascertaining appropriate data may be thought-provoking for scientists across all the academic disciplines (Yoon and Kim, 2017), nonetheless, it is particularly tough for social scientists since data are dispersed between countless sources and programs (Curty, Yoon, Jeng, & Qin, 2016). Furthermore, each discipline's practice of sharing varies in terms of the capacity of data created, alleged importance of sharing, moral restrictions to mention but a few (Robinson – García, Jiménez – Contreras, & Torres – Salinas, 2016). Findings from the literatures revealed that scientists share their data more than their counterparts in the social sciences.

2.7.1 Data Sharing in Social Science Disciplines

Scientific data signifies those raw and basic data normally gain through scientific activities such as experiment, observation, detection, survey (Si, Xing, Zhuang, Hua, & Zhou, 2015). Data sharing occurred in different ways in the social science, ranging from informal dissemination with often known peers to formal repositories. There is no harmony concerning the meaning of the concept "data" among the social science scholars, which is commonly known as numeric accounts creating from social science approaches and or managerial records, where data are created (Babbie, 2015). By this definition, social science mostly used quantitative form of data, most of the social science data contain explanations on human subjects and unstructured formats for instance, interview, transcript and many related themes (Yoon and Kim, 2017).

Recently, there is development in the social science as numerous researches are conducted on open access and data reuse by the social scientists (Curty, 2016; Frank, Kriesberg, Yakel, & Faniel, 2015). With the hope to clearly understand social scientists' data sharing practices. A lot of social sciences disciplines including economics, sociology, and political science were no doubt some of the earliest disciplines that involved in research data sharing via journal data sharing policies (Kim and Adler, 2015). (Miguel et al., 2014) asserts that the present open science practice among social sciences scholars is due to the manner in their fields of research which frequently needs huge volume of exclusive data collected over time. Furthermore, unlike the sciences, in social sciences data sharing are bound by certain rules and or sometime agreements concerning the privacy, law and moral concerns (Carter, Laurie, & Dixon-Woods, 2015). Yet, these disciplines attached more values to data sharing as a result of massive increase in the availability of informative social science data (Shah, Cappella, & Neuman, 2015). Here, data sharing service is mostly delivered by various longstanding data archives: for example, the Inter-University Consortium for political Social Research was originated in 1962 (Zenk-Möltgen & Lepthien, 2014) and the GESIS Data Archive for the Social Sciences was founded in 1960 (Recker, Zenk-Möltgen, & Mauer, 2017). Were all involved in providing services of research data sharing to other social sciences scholars.

Although the social sciences were late adopters of technology, they have expressed interest in using technology in getting access to other data such as unpublished research, conference papers and even technical reports (Kim and Stanton, 2016). Considering the availability of data sharing technology, it is expected that data sharing among social sciences will be more prominent. However, studies revealed the reverse is the case, despite the increase awareness of the important of shared data, absent of suitable policies and principles across the social science disciplines made sharing become uncommon practice among social scientists (Kim and Adler, 2015). Another study conducted showed respondents in the sciences welcome sharing practices as compare to their colleagues in the social sciences where human subjects and other constraints may originate and affect datasets (Zenk-Möltgen and Lepthien, 2014). King, argued that political science is a community enterprise which needs access to data to replicate the existing studies for easy understand but the benefits of that sharing was demoralized by infrastructural faults in handling the enormous types and sizes of data (King, 2014).

Social scientists specifically sociologists essentially recommend a sequence of activities which academic librarians can take to inspire data storage and sharing. (Cliggett, 2015) has deliberated some of the worries particularly to Anthropology and disputes that anthropologists have some moral and professional responsibility to share their research data. (Curty, 2015) discovered that reuse among social scientists' investigators are largely influenced by perceived benefits attached in data recycle.

2.7.2 Data Sharing in Science Disciplines

The amount of data created in the sciences is undoubtedly rising at an immense rate and the size of individual data sets is increasing massively. In fact, much of the present data sharing research deals with the sciences more broadly, depriving or given less emphasis on the social sciences (Cooper, 2018; Kim and Adler, 2015). In natural science, scientists authenticate earlier research by peer review of the original data (Borgman, 2012). To scientists, by scrutinizing the original data, they can indorse or repudiate research findings, which aids avert scientific blunders or misconducts like deception or pick out reporting. Scientists through data sharing trial new hypotheses, prepare meta analyses which ultimately result to scientific innovation (Irawan & Rachmi, 2018).

Scientists use shared data to train their science trainees, also lead them have confidence that such free available data, publication and other materials are critical tools for enlightening their students (Kim and Adler, 2015). Consequently, researchers' attitudes and practices towards sharing data in sciences vary by individual discipline as well. Some branches in science like astronomy, physics have well established culture and experiences of sharing research data their colleague (Kim and Stanton, 2013).

Generally, researchers in respective of their fields own diverse approaches and beliefs for handling and sharing research data (Hall, 2013; Huang, Hawkins, & Qiao, 2013). But again encounter various problems in controlling data especially from several sub disciplines in sciences (Yang et al., 2017). The support by funders and journals is increasingly encouraged data sharing practices particularly in sciences (Mennes, Biswal, Castellanos, & Milham, 2013). To the extent that some science based societies decide to fund project with the aim of rescuing data that had originally denied been shared (Hsu, Martin, McElroy, Litwin-Miller, & Kim, 2015). Therefore, connectivity among science subjects has augmented development in worldwide research and estimates designate scientific output is doubling approximately every ten years (Gonzalez & Peres-Neto, 2015).

Certain things usually encourage scientists more to share data as the results of their research can be well tested, reducing to the minimal level mistakes and fraud that may occur (Sandve, Nekrutenko, Taylor, & Hovig, 2013). Hence, science finally became more replicable and efficient. To say it all, most of the scientific disciplines created databases that accommodate a lot of data. For instance, many astronomical institutes are associated with a well-developed data repository that hold huge amount of data (Kim and Stanton, 2013).

2.8 The Research Gaps

Bearing in mind the results and various analysis of these previous studies offer appreciable vision, however, concerning some important areas like theoretical framework used and the kind of theory employed, certain limitations can be identified. To start with the theoretical model, most of the previous studies are far away from using any vibrant theoretical model that can vividly explain the research data sharing practices among academics. Less theoretical models were seen in the process of consulting previous studies that cannot successfully guide future data sharing researchers.

Again, previous studies concentrated more on benefits, barriers, reason for data withholding and factors influencing data sharing among scholars (Horton & Katsanidou, 2011). Quite a number of the prior researches concentrated primarily on either individual, institutional or other factors that are influencing research data sharing neglecting how data sharing is perceived and some sensitive factors such as organizational supports and social factors. Although most of these studies came from Europe, America or Asia, these continents are less affected by organizational supports and social factors. Nonetheless, (Tenopir et al., 2011) pointed out that those factors are not enough for effective research data sharing hence the need for other activities like practices and culture and the way researchers views the concept is necessary. Since researchers' data sharing practices is influenced by factors as such organizational supports and social factors, future researchers need to ponder on those factors as well.

Similarly, prior studies did not cover much on some significant disciplines such as the social sciences and humanity in regards to research data sharing with very research from those field. Much of the previous studies only reflect on physical or life scientists then psychologists to be precise, instead of medicine and social sciences disciplines that deal with human subjects. This result to the less data sharing in these neglected areas as ascertained by another study conducted showed respondents in the sciences welcome sharing practices as compare to their colleagues in the social sciences where human subjects and other constraints may originate and affect datasets (Zenk-Möltgen and Lepthien, 2014). Research data sharing practices cannot be experienced and would remain incomplete without considering some disciplines that have vast scholars. Therefore, further exploration is required to comprehend the real image of research data sharing between varied fields found in the academic communities.

Nevertheless, research methods used by the previous researches are enormous, but seem to be one sided as survey was the dominant method employed. For this reason, greatest number of the existing materials on research data sharing practices are mainly restricted to data associated to the survey method. To have a deep and well established investigation on the general research data sharing practices in the academic communities, future research without any piece of doubt need to cogitate either qualitative method or preferable mixed methods to explore research data sharing practices.

Having appreciated the numerous limitations of previous studies, scholars are in better position to design and develop an upright theoretical framework that can use other suitable theories and include other factors such as organizational supports and social factors. It is also our belief that the new theoretical framework would include more disciplines to address the problem of feeling rejected by other fields. In other word, it should be a framework that would involve all, that can permit scholars to examine research data sharing practices in totality transversely all field of studies rather than concentrating on a particular faculty.

In conclusion, the present research would even though employ survey method, yet an interview will be conducted to understand more on how researchers view data sharing as a concept which can give an ample opportunity for the researcher to provide an all-embracing knowledge of research data sharing practices. This framework is hoped to be universal that would give clear image of the term research data sharing practices in academic communities.

2.9 Related Theories

Due to recent growth in research on data sharing, different theories are employed in conducting these researches. Inspiring academics to share data and experience at the institutions of higher learning has recently gained attentions among the researchers. In order to promote data sharing behavior, academics need to recognize the influences and the mechanism that drives individually to contribute their research data with other employees. Theory of organizational culture was employed for this study.

i. Theory of Planned Behaviour (TPB)

This is considered among the noticeable theories aim at evaluating individual behaviour. It identified and explained that behaviour is a product of both the attitude and subjective norm. TPB proposes three separate antecedents control human behavioural intentions to exhibit specific behaviour: attitudes, subjective norms, and perceived behaviour controls (Ajzen, 1991). TPB is perceived to be among the most persuasive and extensively used theories that explain human behaviour in clear-cut perspectives (Arnold et al., 2006; Morris, Marzano, Dandy, & O'Brien, 2012). However, the theory never wholly ponders on either environmental or economic factors which may have consequences on an individual's intention to accomplish a behavior (Guo et al., 2018). The theory of planned behaviour offers discernments about the way people's behavioural controls, attitudes as well as subjective norms influence their doings. Thus cannot be properly employed in the present research.

In this theory, the key components that describe individual behaviour are attitude, subject norm and perceived behavioural control. Thus, to start with, firstly, attitude towards a particular behaviour has been found to predict individual's intention to perform that behaviour (Verma & Chandra, 2018). Previous empirical studies support the connection concerning attitude and behavioral intention. For instance, in literature on knowledge sharing, attitude was studied and discovered to have positive significantly impact on behavioural intention to share knowledge (Bock, Zmud, Kim, & Lee, 2005). Again, in his research (Kim, 2013) considered attitudinal beliefs to be more important motivational factors influencing scientist's data sharing behaviours.

Secondly, different studies have studied subjective norms and discovered to inspire individual's intention to perform certain task. For example, in the area of technology adoption, (Huang, Teo, Sánchez-Prieto, García-Peñalvo, & Olmos-Migueláñez, 2019) in marketing (Bleize & Antheunis, 2019) and in the area of knowledge sharing (Anwar, Rehman, Wang, & Salleh, 2018). Anwar, Rehman, Wang, and Salleh, (2018) revealed that subjective norms absolutely has impact on physicians' intention to keep knowledge available to others via direct and indirect paths. Conversely, in the surviving literature concerning sharing data, investigators rarely undertaken research on how subjective norms motivate scientist' data sharing behaviours.

Thirdly, the concept of perceived behaviour control means to people's perceptions of how they could conduct a specific behaviour and the extent of control they need to have over the behaviour (Ajzen, 1991). Perceived behavioural control was familiarized to enlighten circumstances where people have absence of control regarding their targeting behaviours (Norman, 2018) claimed that if a behaviour is not well-regulated, people may not possible accomplish it. Perceived behavioural control was also found to have preceding the intention to share knowledge (Hossain & Kim, 2018). Even though theory of planned behaviour carefully explained individual's inspirations and activities, it is associated with certain limitations for example, theory of planned behaviour only considers personal factors instead including both organizational or even social factors (Bada, Sasse, & Nurse, 2019). This theory even though is perceived to be individual level theory, it refused to conveniently explain scientist's data sharing behaviour (Kim, 2013). Thus, may not be suitable to the present study.

ii. Institutional Theory

Institutional theory is a theory reflecting on social structures. Institutional theorists assert that the institutional environment can strongly influence the development of formal structures in an organization. Institutional theory has become a dominant perspective in macro organization theory (Kostova & Marano, 2019). It considers the processes by which structure, rules and norms are established as authoritative guidelines for social behaviour. Institutional theory provides a rich, complex view of organizations, however, has little attention paid to the role of human agency in institutional changes.

In decades, there is an evolved in institutional theory with extended scope to incorporates individual's as well as organizations (Alvesson & Spicer, 2019). Institutional theory surely offered momentous intuitions on how social actors are influenced by institutional forces within their institutional atmosphere. To this theory, social actors face external pressures to confirm with shared notions of needed and proper behaviour to obtain means and own social backing by noticing organizational legitimacy (Wang, Wei, Qiao, Lin, & Chen, 2018). Institutional theory further acknowledged an institutional surrounding offers social opportunities and standards, letting social actors to achieve satisfactory behaviours, improve socially satisfactory practices, and make appropriate organizational processes (Scott, 2005). Institutional theory explains the regulative, normative and cultural-cognitive pressures on individual behaviours.

Prior studies found that the above pressures are significant mechanisms to influence appropriate and legitimate behaviour in an organization (Greve & Teh, 2018). For example, regulative pressures stem from diverse sources such as organizations, parent corporations and regulatory bodies. Previous studies revealed that researchers claimed that institutional theory can practically be related to research on how institutional pressures influence individual's belief, attitude and behaviours (Reviwer, 2018).

iii. Social Exchange Theory

Social exchange theory this theory studies the social behaviour which involves relationships among employees. This theory advocates that social behaviour happened when there is exchange procedure. This exchange occurred as a result of greater benefits and lessen costs. That individuals evaluate the possible reimbursements and dangers of social relationship. However, this theory is focusing too much on the institutional perspectives and ignoring social aspects of the relationships such as how partners communicate and interest in shared events (Zellweger, Chrisman, Chua, & Steier, 2019).

Conversely, social exchange theory can be regarded to have been offering an economic back up to social interactions.

Social exchange theory posits that individual engage in social interaction based on an expectation that it will lead in some way to social rewards such as approval, status and respect (Landor & Barr, 2018) This implies that an individual can benefit from active participant with others and enhance his or her personal reputation. Increase in reputation remain a key for individual achieving in an organization which control and maintain status within a particular community (Harrison, Boivie, Sharp, & Gentry, 2018). Results from previous studies revealed that practices are consistent with social exchange theory and offer evidence that building reputation is a strong motivator for active participation (Wang, Xiang, Yang, & Ma, 2019). In information sharing for example, the chance to increase one's reputation depend on how a person share his information to others. Therefore, the perception that that contributing information will enhance one's reputation and status in the profession may motivate individuals to contribute their valuable, personal information to others in the organization (Mojdeh, Head, & El Shamy, 2018).

Previous literatures showed the influences of these theories on this study. for example, theory of planned behaviour describes how individual belief influence their intention to do things. Theory of planned behaviour affords understanding concerning how an individual's attitudes, subjective norms and perceived behavioural control influenced their behaviour (Ajzen, 1991). Institutional theory provides significant insights about how social actors such as culture influenced human activities in an organization via institutional pressures (Powell & Di Maggio, 1983). For social exchange theory, recent literature reveals social influence has largely been examined from a socio-psychological perceptive and it often defined according to its effects on individual attitudes and intentions towards a certain behaviour (Wu & Wang, 2011). Thus, all these theories acknowledged that attitude, subjective norms, perceived behavioral control, and exchange of maximizing benefits and minimize cost in turn leads to drive academics towards sharing behavior (Razak, Pangil, Zin, Yunus, & Asnawi, 2016). This study use theory of organizational culture to understand the data sharing practices of academics.

iv Theory of Organizational Culture

The concept "Organization culture" denotes to the values and beliefs of a given organization. It is the culture of a particular institute which decides the way persons interrelate with each other and act with individuals outside their territory. Organizational culture theory helps in guiding scholars' attentions concerning an extensive understanding of organizations (Mumby, 1988). This study used Shein 1990, who considered organizational culture as a multi-level construct that integrates analysis in relation to three conceptual levels which are: Artefacts, espoused beliefs and values and basic underlying assumptions. These three layers suited the constructs of this study.

Artefacts level of organizational culture- this is seen as a noticeable expressions of culture like structures, practices and processes, rituals, technology, manner of dress and language. They are things that can be seen, heard and felt they include constructs like organizational structure, infrastructure, data repository, funding agencies, journal publishers and policy / guidelines.

Espoused beliefs and values of organizational culture- (Schein, 1990) describes this level as eyeing for a motive behind any observed artefact. Example of such factors are creativity, problem solving and relating with others. Constructs under this include; conditions for data sharing, perceived effort, anticipated benefits, legitimate concern, altruism.

The underlying assumptions level of organizational culture- these assumptions are being described as an unconscious features of organization culture which include elements like perceptions, thoughts and feelings, and these assumptions are very hard to change (Schein, 1990). They involved community culture and discipline norms.

Theoretically, there are related studies that employed theory of organizational culture that are related with the present research and one of this study is Espoused organizational culture

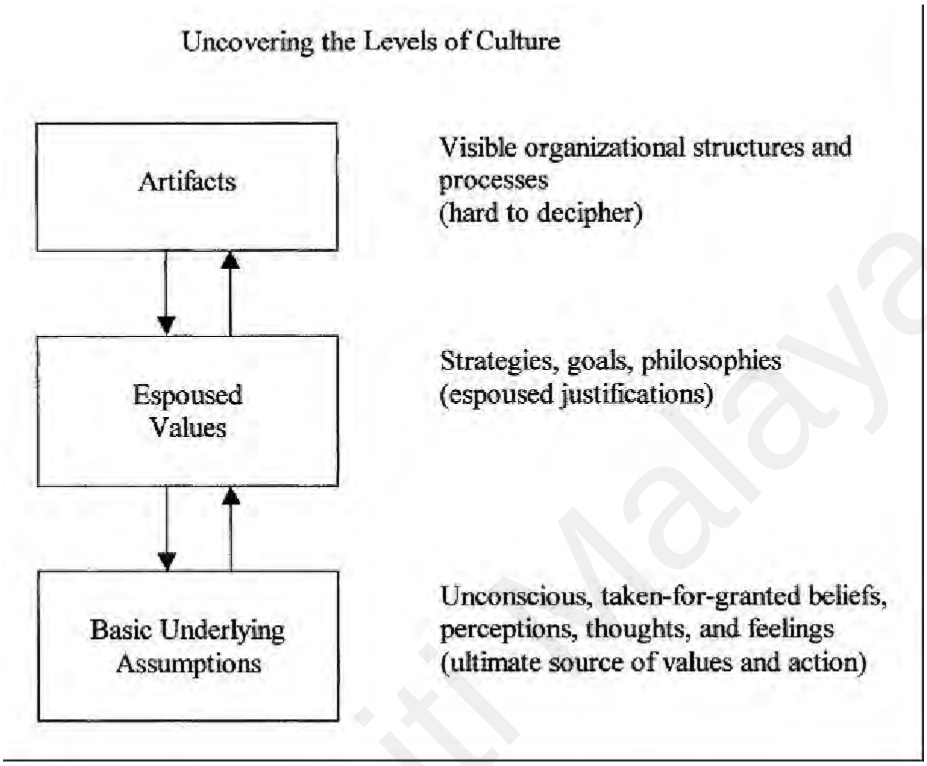

Figure 2.1: Model of Organizational Culture Adapted from Schein, 1985

Values as antecedents of internet technology adoption in an emerging economy. Both studies considered culture as shared values and belief of individual within a given organization. These studies also found espoused cultural traits influence individual behaviour. The studies were both piloted within the background of rising countries (Indian and Nigeria) and most of the literature consulted are within the setting of industrialized countries. Another research related to the present research context is the Positioning organizational culture in knowledge management research. Both studies attempt to identify the role of organizational culture and to expand sharing research. They provide insight into the impact of organizational culture on knowledge management process and potential implications of organizational culture towards sharing are elaborated.

There are a number of theories that are related to sharing in an organization including theory of organizational culture (TOC). Other theories comprised theory of planned behavior, institutional theory and social exchange theory among others.

2.10 Summary

For thoughtful understand of research data sharing in academic communities, current research deliberates on the open science generally, applied theory of organizational culture and explains data sharing practices between different disciplines. Researchers have viewed the concept differently from various disciplines, but virtually their believed is a fundamental mechanism for transparency. Data sharing is seen as the fundamental mechanism for transparency. Fully explanations regarding the way and manner academics practicing their data sharing from different fields were delivered in which materials on both data sharing and data withholding were accessed. The term data sharing was considered as that situation that allows data used for scholarly research freely to others researchers, while the concept data withholding denotes declining the provision of data to other investigators as expected through various methods. Long before now, researchers have been busy sharing their papers, presently they need to capitalize on sharing their data. Occurrence of data sharing and data withholding among academic communities was also discussed. Various studies revealed the benefits and barriers of sharing research data and the level to which researchers share or withhold their data.

Differences in research data sharing practices between social sciences and sciences were also deliberated in this research. A number of studies investigated sharing practices among different disciplines but failed to separate between the two distinct faculties, that is sciences and social sciences and this work provided. This research finally showed the various disparities among the two faculties and also indicated that each discipline practice data sharing varies in terms of the capacity of data created, alleged importance of sharing, moral restrictions and many more.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Overview

Research methodology is about the steps taken on how to answer a set of research questions and research objectives. For this study, a survey research methodology is adopted, as this approach helps to provide standardized information to describe variables or to study relationships between variables. The study explored using semi-structured interview and survey questionnaire on data sharing practices of research data sharing among academics. The examination of research questions transpired by way of two interrelated investigations: firstly, interviews with the aim to examine how academic community perceive the concept of data sharing, and secondly, survey research to investigate the factors that influence academics' data sharing practices in Nigeria and to also investigate the distinctions in data sharing practices among two disciplines.

3.2 Research Design

Research design describes as the processes of collecting data, analyzing data, and reporting results in research. It is known as a procedural plan which adopted by researchers to answer the question accurately and validly (Anjana et al., 2011). A sequence of rational decision-making selections symbolizes a research design outline and clarifies the steps that connect philosophical assumptions to precise methods (Creswell, 2011). It includes the procedure of describing the research problem, formulating hypotheses; gathering, establishing and evaluating data; making deductions and reaching conclusions; and finally testing the conclusions to determine whether they fit the formulated hypotheses (Kothari, 2004).

In this study, a quantitative was employed. For an in-depth investigation of the context of the perception and practices of research data sharing among academics, a semi-structured interview was also conducted. Semi-structured interviews were held with 22 academics who are senior researchers with data sharing experiences. The aim of the interviews was to answer the research question 1, How does Nigerian academic communities perceive data sharing? research question 2, What are the motivations of research data sharing to academics? And research question 3, What are the perceived risks for academics sharing their research data? Secondly, a survey was accompanied to explore those issues that affect academics' data sharing practices and examine the differences in research data sharing between social sciences and sciences disciplines. It is pertinent to explain why this research methodology remained quantitative despite conducting interviews. The aim of the interview was to develop the survey instrument by answering research question 1 to 3. There was no prolonged engagement with the participants, and no triangulation methods was used to qualify this as qualitative research design.

Figure 3.1 displays the indication of the research design showed in the present research.

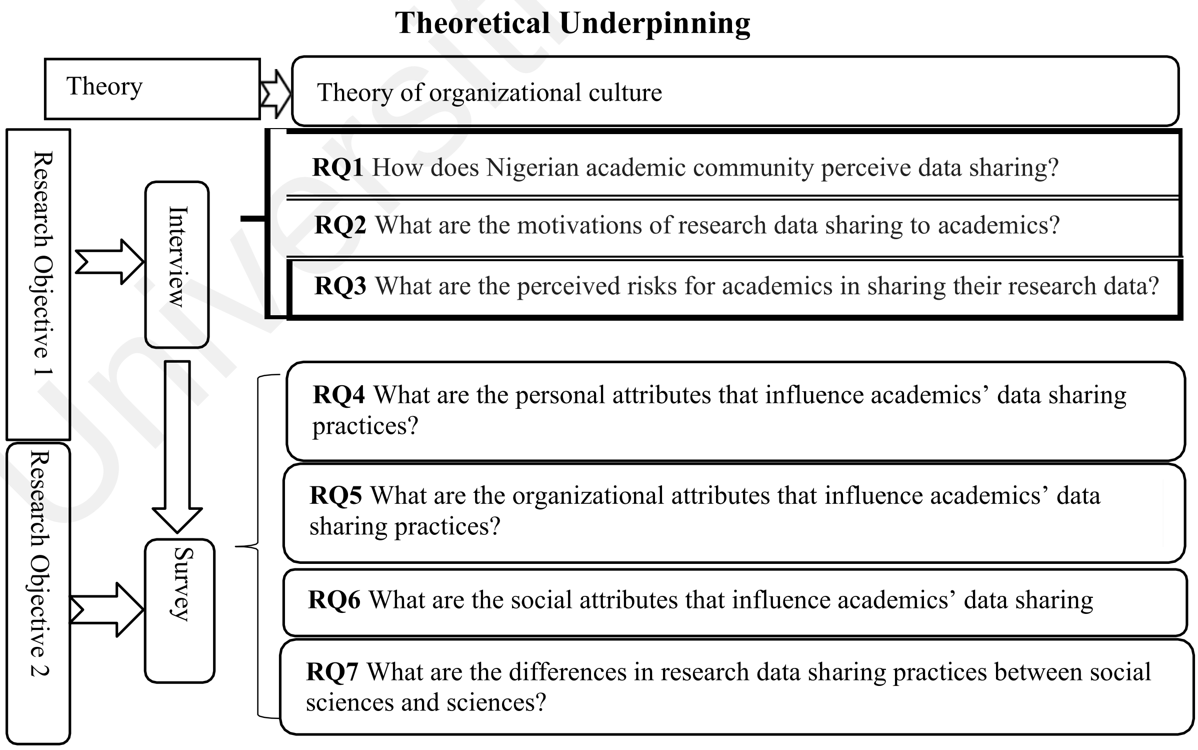

Figure 3.1: Example: Overview of the Research Design Conducted in this Study

3.3 Theoretical Framework

Theory of organizational culture (TOC) which represents collective values, beliefs and principles of organizational members by Schein, 1990 was used in this study. Organizational culture deals with culture of a particular institute which decides the way persons interrelate with each other and act with individuals outside their territory. Organizational culture theory turns out to be a main theoretical rallying point, which helped in guiding scholars' attentions concerning an extensive understanding of organizations. The theoretical ideologies of the theory highlight that organizational lifecycle is complex and that investigators need to put into consideration not only the people in the organization rather should include their perceptions, behaviors, activities, and stories.

A prominent author, Schein, 1985 explained the concept of organizational culture as a multi-level construct that integrates analysis in relation to three conceptual levels which are: i. Artefacts, ii. espoused beliefs and values and iii. basic underlying assumptions. The three layers described by Schein had matched the variables found in this study.

i. Justifications of using theory of organizational culture

The use of organizational culture in this study is desirable looking at how Schein, 1990 categorized the theory in to three layers (artefacts, espoused beliefs and values and basic underlying assumptions) that well-matched the variables found in this study. These constructs are organizational structure, infrastructure, data repository, funding agencies, journal publishers, and policy / guidelines, (Artefact). conditions for data sharing, perceived effort, anticipated benefits, legitimate concern, and altruism (espoused belief and values). Community culture and discipline norms (basic underlying assumptions).

The present study is about sharing among people in a given organization and So understanding the organizational culture encourages discussions and sharing of information of any kind amongst researchers from different disciplines. Theory of organizational culture is seen as an outline by which people understand the world they are that explains how human beings interrelate within a given organization in respective of its size. Community, no matter how large or small it's culture controls how individuals will act or react to new conditions or information as they view it in the context of what they already know. Understanding organizational culture will aid in identifying the underlying causes for resistance to any form of sharing. Organizational culture has been described as a complex entity of values, beliefs, behavior norms, meanings and practices shared by personnel within an establishment (Hoogervorst, van der Flier, & Koopman, 2004). Thus, the use of this theory for researcher on sharing among researchers is appropriate.

Theory of organizational culture sees sharing and interactions between two or more people who believe to have, to some degree certain things of value to each other, and are ready to share it. This theory become suitable to many researches relating to sharing because the theory stressed the notion of relationship among people (Williams, Manwell, Konrad, & Linzer, 2007). Since the theorists' effort is grounded on actual organizations with real employees, the researchers have made the theory more applicable and useful.

Both interview and survey method are conducted, interview was conducted to give more information in reforming the survey instrument to answer the research question four (4) to research question seven (7).

3.4 Interview

An interview has been described as that conversation which involved asking questions and given answer to that question (Mish, 2004). It is a situation that includes one on one conversation among an interviewer and an interviewee. There was an interview with the scholars from diverse fields of study to answer research question 1, 2, and 3. The interview was used in the development of the survey instrument. This was also used to understand how they perceive the concept "data sharing" and to also comprehend how scholars share data with colleagues and investigating the influence of such sharing among themselves.

3.4.1 Interview Guide

In research, before conducting interviews, the researcher needs to develop an interview guide that can use to help the researcher directs the conversation focuses to achieve the research objective (s). An interview guide lists the questions that are to be revealed in the progress of an interview (Jacob & Furgerson, 2012). These guides differ from highly scripted to relatively loose, however it shares similar characteristics: They support researcher be acquainted with those questions to be asked and how to position the set questions, and also in what way to ask follow-ups. Interview guides also offer direction on what the researcher may possibly ask again, after the interviewee has responded the latter question. The researcher developed interview guide questions on data sharing practices among academics as pointed out.

RQ1. How does Nigerian academic community perceive data sharing? Under this research question, the following interview guides were formulated:

- How would you describe your perceptions towards research data sharing?
- How does your discipline make you know about research data sharing?
- How do you become aware of research data sharing?
- What is your understanding about research data sharing?
- What platform do you use for research data sharing?

RQ2. What are the motivations of research data sharing to academics?

- What motivate you to share research data sharing?
- How does expected rewards motivate you to share data?
- What are the other benefits you expect in sharing your data?

RO3. What are the perceived risks for academics in sharing their research data?

- Are there risks in sharing research data?
- How did you consider sharing research data as a risk?
- Why do you withhold your data?

3.4.2 Population and Sample Technique

a. Population

The academic staff of the Nigerian universities constitute the population of this study. The population of the interview respondents include all the 22 head of departments (HOD) in the 5 universities under study. It is significant to note that there are six (6) federal universities spread across the North east Nigeria (Akintoye & Uhunmwuangho, 2018). For security reason, one of the universities (university of Maiduguri) was not covered thus, five (5) universities were covered for this research. The universities under study have a total of twenty-two faculties and a total of seven thousand five hundred and sixty-one (7561) academics. These five universities do not include state or private universities, this is for the fact that there is disparity in funding pattern and focus of proprietors may not make it possible to be part of this study. At least one university is located in each of the state capital therefore, making up to five universities for consideration. There are twenty-two participants in which every participant represents his or her faculty for the interview.

b. Sample and sampling technique

Purposive sampling technique was employed and 22 head of departments (HODs) were chosen as the respondents as each respondent represents his or her department. This particular sampling normally emphasizes in certain features of a population that are of interest, as all respondents are heads of departments, they are selected because they fit a particular profile. Therefore, the respondents were purposely chosen based on their experience, knowledge their willingness to participate in the study. These categories of respondents can best support the researcher in addressing the research questions. The main target for this sampling is not to represent the whole population but to get sufficient information that can help in achieving the aim of the study.

3.4.3 Preliminary Study

For the purpose of preliminary study, a single university was covered with a total number of five (5) faculties and a total of two thousand and ninety-eight (2098) academics. In order to have rich data for this research, the research used head of the faculties (Deans) to serve as the respondents. Chosen these respondents was assumed to mean selecting the more experienced academics in terms of research data sharing and would likely generate rich data for the study. This selected approach was described as "purposive sampling" and that it assumes the researcher of rich data. Purposely sampling was also described as a judgmental sampling where the researcher decides who best can give rich data considering their weight of familiarity with issues and knowledge (Robinson, 2014). The researcher sent a consent letter to all the respondents and the respondents called the researcher on the mobile number provided on the letter, a consent can be seen attached in appendix A. That led to a schedule of the various meeting for the interviews in the respondents' offices.

3.4.4 Data Collection

Collection of data is more significant in research, as the conclusion of any study are based on the data collected. There was a single session interview with the duration of 25 to 30 minutes, the sample of the interview questions was attached in appendix B. The interview was audio recorded with the respondents' permission. The participants were purposively chosen among many researchers within the scope of the research. The researcher accompanied a total of 22 interview sessions, whereas an individual participant was interviewed just once. There is a single session for the interview with the duration is from 25 to 30 minutes. The least period for each interview is 25 minutes and the supreme period is 30 minutes. The researcher commenced the interview by a warming-up dialogue in which he made a light introduction of himself and the questions that may be expected. The researcher further made participation voluntary and at suitable time and convenient places. The interviews were handled at a different scene depending on where the participants chosen which include offices or home. By so doing, participants were able to react to the interview in a comfortable situation which prepared them more ready for the interview.

An initial step for the interview commenced by requiring the participants to be conversant and read the consent letter before fully partaking in the interview. This letter comprised clear information to the interview participants concerning the study. In the process of steering the interview, the researcher explains each and every procedure to the participant and how their involvement in this study is imperative. The research also notifies them on the confidentiality of the interview by telling the participants that their response will be treated privately and anonymity. Consequently, interview data was first collected as it is useful in generating and guiding the survey instrument.

3.4.5 Validity and Reliability

Generally, validity and reliability are key aspects of every research, it is the strength of research and a sensitive issue that every researcher should be aware. The purpose of validity and reliability is determining whether the findings are accurate and aid to assuring that other investigators agree outcomes as reliable and truthful. This is especially significant when interview was conducted because interview research results are frequently seen with suspicion by other investigators. Thus, interview transcripts were returned to the participants to verify the content. Also, peer checkers were used in the analysis of the data. To determine the validity of data, the researcher has gotten the assistance and cooperation of two of his friends who are also academics to serve as peer checkers. These peer checkers have been incorporated and given a complete transcript of the interview, which consisted all participants. They have helped in highlighting the importance ideas to be checked and reviewed.

The concept of reliability on the other hand is concerned with the consistency, dependability and repeatability of the informant's accounts as well as the capability of the investigator to collect and record information correctly. It means the ability of a research method to provide consistently the same results over repeated testing periods. Similarly, it requires that a researcher using the same or comparable methods achieved the same results every time he uses the methods on the same or comparable subjects (Brink, 1993). Current study guarantees reliability regarding the test and retest issue and internal consistency. Each construct's reliability assessment was completed through checking internal consistency of variables. Concerning statistical method, the current research uses Smart PLS as the internal consistency measure indicator.

The researcher used the following strategies to ensure the reliability of the interview findings;

i. The researcher was able to provide worthy verbatim explanations of participant's accounts to back findings.
ii. The researcher also proven clarity in terms of thoughts processes during data analysis and subsequent interpretations.
iii. There was respondents' validation, this means the researcher requested participants to comment on the interview transcript and whether the final themes and subthemes created adequately reflect the phenomena being investigated.

3.4.6 Ethics

The researcher was committed to safeguard the anonymity of research participants by not written their names or actual department. All participants voluntarily involved in the research by undergoing an informed consent process. This help the participants to confirm and understood their involvement in the study so they could determine if they wished to participate.

3.4.7 Data Analysis

The researcher used thematic analysis to identify information from words drew from the participants. Data were coded manually and also there was a thematic analysis to generate themes. The audiotaped data from each interview are transformed into transcripts. Some of this information is used in developing a research framework.

The next section offers the themes generated from the interview data. Normally, the analysis of the interview data is driven by the current study objective which is to examine research data sharing perceptions and practice among academics. Each of these themes were discussed separately by giving from quotations from some of the responses by the face to face interview respondents and relating it to main findings from the literature.

Open Coding: The first stage of data analysis is open coding. At this stage, the data are first broken apart line-by-line or segment-by-segment. The data are then labeled with a concept that expresses the researcher's interpretation of what was being expressed in that particular segment of the data. During open coding, all of the concepts are temporary and modifiable while the incoming new data are analyzed. These steps were repeated throughout the interviews. The concepts that came from the initial interview were developed and validated during the next interview and data analysis process. The interview data were coded using the same concept labels. Any new concepts were added into the list of codes. After fifteen interviews, it appeared that data saturation had been reached. No new ideas were being discovered and the repetitions of the initial categories were continued with the last seven participants, bringing the total interviews transcribed and coded to 22. Five themes and subthemes with examples of direct quotes were taken from the data.

Thematic data analysis: This is normally applied in qualitative research and emphases on observing themes inside data. It stresses identifying, scrutinizing, and recording themes within data. The term thematic analysis goes beyond simply counting expressions orwords in a text and moves on to identifying implicit and explicit ideas within the data. The raw data for this research comprised the transcripts that came from the audiotapes of the interviews.

3.5 Survey

The concept of survey research has been to be the gathering of information from a sample of persons by means of their answers to enquiries (Check & Schutt, 2012). This kind of study tolerates various methods to recruit respondents, accumulate and apply numerous approaches of instrumentation. The major aim of this form of method was to acquire information describing characteristics of a large sample of individuals of interest relatively quickly. Survey was used to answer question 4, what are the personal attributes that influence academics' data sharing practices? question 5, what are the organisational attributes that influence academics' data sharing practices? Question 6, what are the social attributes that influence academics' data sharing practices? that examine the factors of data sharing among academics in diverse academic disciplines and question 7 what are the differences in research data sharing practices between social sciences and sciences? and to see the differences between sciences and social sciences data sharing practices.

As revealed in Figure 3.4 which comprised all the constructs in this study. These variables are generated from both literature and interviews. Though, most of the variables are gotten from the literature some of them are mentioned by the interview participants. The variables generated from the interview are community culture, infrastructure, perceived effort, legitimate concern and conditions for data sharing the remaining variables are from the literature alone. Even though some variables found from the interview are equally traced from the literature.

3.5.1 Framework for the instrument development

The framework of the current study was based on the theory of organizational culture proposed by Schein, which was positioned in to three layers. There are two frameworks (initial and the modified). The initial framework can be viewed as the ordinary sketch that showed how theory of organizational culture is connected with the three attributes as the independent variables and data sharing practices as the dependent variables.

The original framework shown in the Figure 3.1, encompassed the three layers of the theory of organizational culture as stated by which are appropriate with the three attributes identified in this study.

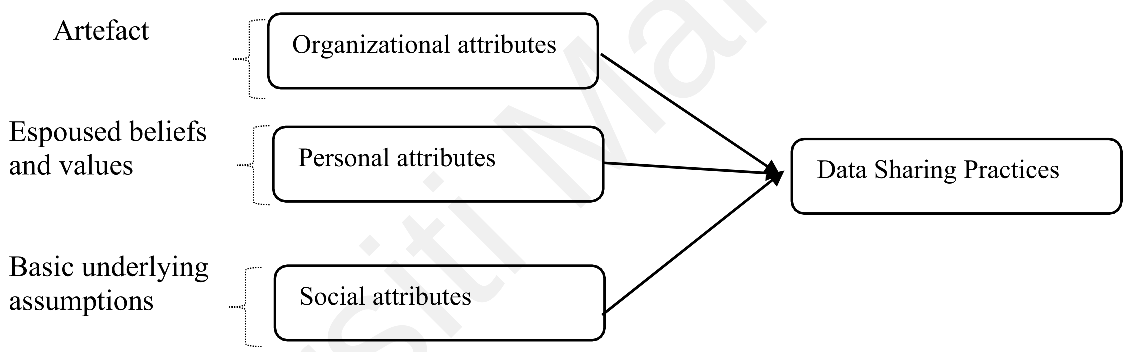

Figure 3.2: Conceptual Framework

The modified version of the research framework displayed in Figure 3.2 comprised all the variables in this study. These variables are generated from both literature and interviews. Though, most of the variables are gotten from the literature some of them are mentioned by the interview participants. The variables generated from the interview are community culture, infrastructure, perceived effort, legitimate concern and conditions for data sharing the remaining variables are from the literature alone. Even though some variables found from the interview are equally traced from the literature.

3.5.2 Variables and Hypotheses Development

Basically, there are thirteen 13 independent variables that comprised of organizational structure, infrastructure, data repository, research funders, perceived pressure by journal, policy/guidelines, community belief, disciplinary norms, conditions for data sharing, effort expectancy, expected rewards, legitimate concerns and Beneficence. and one 1 dependent variable which is data sharing practices (DSP) in this study. The following figure showed the hypotheses development of this study.

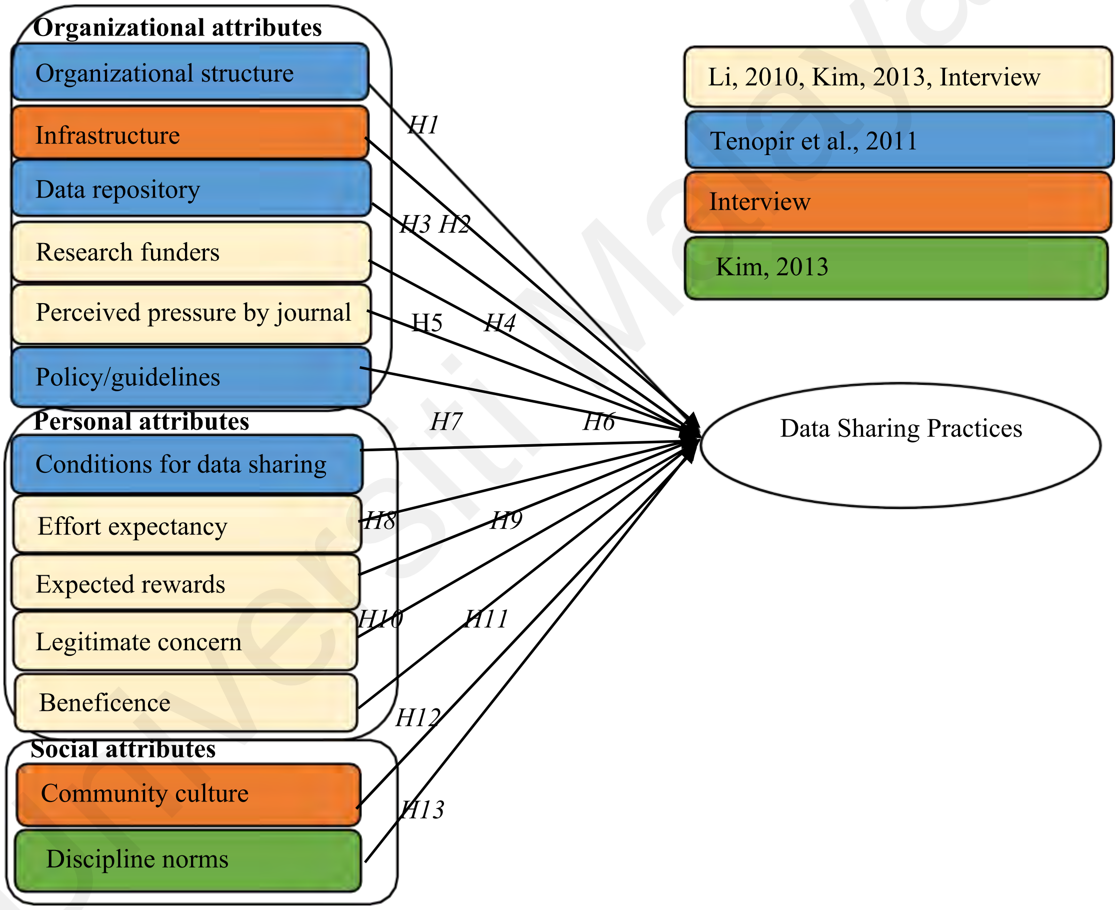

Figure 3.3: The Research Framework

a. Definitions of the Variables

Research variables are grouped based on the three attributes (Organizational, personal and social attributes).

1. Organizational Attributes

i. Organizational Structure

This construct is described as the structure and operational processes of an organization (Marcoulides & Heck, 1993). Structure of any given organization can determine the level of participation in sharing data. Thus, organization with organized structure can positively influence data sharing practices among its staff. To attain this vision therefore, some of the utmost significant and usual organizational structure measurements like coordination, centralization, formalization and specialization need to be reexamined and evaluate their impact on data sharing practices.

ii. Infrastructure

Infrastructure are the basic physical and organizational structures and facilities (Stevenson, 2010). Are substructures that would encourage and improve data sharing exercise such as training, platforms, and connectivity. Having infrastructure in an organization can positively determine their data sharing practices. For example, an organization that provide adequate platform for its staff to improve their research would encourage sharing of research data results. Previous study indicated that provision of tools such as intranets, online professional blog and other related platforms increased cooperation and sharing among researchers.

iii. Data Repository

Data repository is a concept denote to a destination chosen for data storage (Barbosa, Sadre, Pras, & van de Meent, 2010). Having functional organizational data repository is considered to positively influence the academics' data sharing practices. Data repository can simple be described as a destination designated for data storage. Current development in the area of technologies brought about data repositories that enabled researchers to share any available data with their research publications without difficult. It is aimed at storing data for an analytical or reporting purpose.

iv. Research Funders

Research funders refer to any public or private granting research funders that provide fund to researchers or any investigator. In many cases, these agencies employ regulative powers on academics concerning their data sharing practices. They necessitate scholars to share data if they really want to have grant for their research. Certain policies were made by the government funding agencies to necessitate researchers or any grantees to make raw data freely available to other investigators. They normally intensify regulative pressures on researchers by monitoring the financial funds obtainable to them. For this reason, researchers must comply with the agencies' guidelines.

v. Perceived Pressure by Journal

Correspondingly, several journals necessitate authors to share unique data in numerous means, for example, succumbing data to organizational data repositories, and/or sometimes offering data based on demand. Meanwhile, because journals regulate contact to the publication of research articles, they stand to be leading cause of coercion for scholars. Researchers who get extra regulative pressures from journals are reliable to submit and share their data with others.

vi. Policy/Guidelines

Establishing relevant policies or guidelines in organizations universities inclusive can encourage collaboration among the teaming scholars and positively influence academics' data sharing practices. Policies/guidelines can ensure that data are not plundered and owners are properly acknowledged, given much more guarantee for dataset owners on the safety of their datasets provenance on re-use can be determined which resulted in a higher propensity to share (Sayogo & Pardo, 2011).

2. Personal Attributes and Data Sharing

i. Conditions for Data Sharing

Scholars believe that data sharing enhance productivity in research. But they feel These are certain situations that may warrant academics to share data. Scholars believe that data sharing enhance productivity in research hence, placed some conditions before agree to participate in any form of sharing their data.

ii. Effort Expectancy

The way in which academics consider the amount of effort contained within data sharing practices would no doubt harmfully influence their data sharing practices. Effort expectancy simple means anticipated need for extra energy, work or time to be able to share research data with colleagues, for instance, forming and fixing and preparing data demand extra effort. Increase effort, time, and energy involved in data sharing would discourage a lot of researchers or academics from sharing data either direct or indirectly.

iii. Expected rewards

Expected rewards means the process where the researchers feel that data sharing could provide benefits such as increase in citation rate, reputation and recognition through acknowledgement. Whenever there is low or sometime no benefits these scholars are unlikely to share their data with colleagues. Most of the academics consider having series of citations and credits normally increase their academic recognition.

iv. Legitimate Concern

Is a situation where academics consider data sharing as risk that can involve losing publication, misuse and misinterpretation as while as criticism by their peers. Data sharing become concern and put doubt in the mind of researchers whether to involve in data sharing or not.

v. Beneficence

Beneficence is a strong desire to help others out of kindness without expecting any future rewards, it is a decent free gift. It transpires only when researchers are ready to provide aids to other freely. It is the basis for some generally acceptable actions that involved volunteering donation for that, data sharing should be driven by the altruistic purpose of promoting research in academic community.

3. Social Attributes

i. Community Culture

This is the way and manner a community is doing things. Data sharing practices in some organizations is encouraging but most of the communities are unconvinced in making research data freely available to public. Thus, community belief raised a lot of logical as well as sociological concerns. In other words, some community felt uncomfortable to share any valuable items including research data with others.

ii. Discipline Norms

Different disciplines operate data sharing practices differently. Generally speaking, data sharing is not uniform rather it differs from one discipline to another. Thus, some fields of studies placed rules that encourage data sharing practices while few of these disciplines dispirited such practices.

b. Hypothesis Development

Based on the above definition of the variables, the following hypotheses were postulated.

i. Organizational Structure

A study by (Chen, 2007) specifically considered the connection concerning organizational structure and knowledge management facilitated by social interaction (Chen & Huang, 2007). Mulder, 2013 also expressed that the support of data sharing by organizational hierarchy of a particular organization can influence their data sharing practices. Therefore, the following hypothesis was postulated.

H1: Organizational structure positively influences research data sharing.

ii. Infrastructure

Having good policy land effective staff training can as well inspire researchers to sharing their data with their colleagues. During the interview, some researchers complained about lack of basic infrastructure prevent them from sharing data. Therefore, the following hypothesis was postulated.

H2: Infrastructure positively influences research data sharing.

iii. Data Repository

Prior studies have revealed that data repository enhanced data sharing. Collaboration in form of data sharing in academics desperately needs the composition of institutional support like providing data repositories, technological set-up and even interpersonal relations (Kim and Stanton, 2012) Research data transpires in miscellaneous ways, comprising uploading data in data repositories, succumbing data as journal supplements and providing data by means of personal communication methods upon demand (Park & Wolfram, 2017). This permits researchers to deposit their raw data as well as making such data mostly available to everybody who might want to use them. Therefore, the following hypothesis was postulated.

H3: Data repository positively influence data sharing practices in the academic environment.

iv. Research funders

Research funders necessitate scholars to share data if they really want to have grant for their research. Certain policies were made by the government funding agencies to necessitate researchers or any grantees to make raw data freely available to other investigators. They normally intensify regulative stresses on researchers by monitoring the financial funds obtainable to them. For this reason, researchers must comply with the agencies' guidelines. By implication, scholars are subject to coercion from these funding agencies that increase mandate to share data and encourage secondary data analysis (Kim, 2013). Therefore, the following hypothesis was postulated.

H4: Research funders positively influence data sharing practices in the academic environment.

v. Perceived Pressure by Journals

Correspondingly, several journals necessitate authors to share unique data in numerous means, for example, succumbing data to organizational data repositories, and/or sometimes offering data based on demand. Meanwhile, because journal publishers regulate contact to the publication of research articles, they stand to be leading cause of coercion for scholars. Researchers who get extra regulative pressures from journals are reliable to submit and share their data with others. Previous research revealed that academics do agree to deposit their data to repository based on journal publishers' directives (Kim, 2013). These pressures have many effects on researchers' intention and their actual actions unswervingly (Nosek et al., 2015). Consequently, this study believes that the regulative pressures by journal publishers would rightly influence researchers' data sharing practices. Therefore, the following hypothesis was postulated.

H5: Perceived pressure by journals positively influence data sharing practices in the academic environment.

vi. Policy/Guidelines

Some studies and even during my results have indicated that good policies enhance sharing within the scholars. Maintaining data and making data freely available and digestible are usually interrupted by political disturbance (Alam et al., 2015). In United States, the significant of policy is manifested in organizational activities as many successes are attributed to policies and platforms that ensure quantity, quality and accessibility of the data (Vogel, Greiser, & Mattfeld, 2011). Policy created by organizations affect how the employees share their data (Tenopir et al., 2011). Therefore, the following hypothesis was postulated.

H6: Policy/guidelines positively influence data sharing practices in the academic environment.

vii. Conditions for Data Sharing

Scholars believe that data sharing enhance productivity in research. Although most of the researchers claim to be willing at any time to collaborate and share their data, but in reality, give some conditions to be met if they are to really share data (Wallis, Rolando, and Borgman, 2013). Failure to accept such conditions by the researchers makes them not to participate in data sharing. These conditions directly influence how they share their data (Tenopir et al., 2011). Consequently, the subsequent hypothesis was assumed.

H7: Conditions for data sharing negatively influence data sharing practices in the academic environment.

viii. Effort Expectancy

Earlier studies testified that academics' opinions on effort (extra energy, time and work) for data sharing discourage their data sharing practices. For example, the preparation for data sharing practices required a lot of time and effort which become a factor preventing researchers' data sharing exercise (Kim and Adler, 2015). A significant factor influences researchers' data sharing practices. Correspondently, researchers also consider data request as another thing that make them panic because scholars must have to spend a substantial time give a talk on these requests (Spallek et al., 2019). The time and effort required to share data affect negatively scholars' data sharing especially when they are to make it online since most of them lack time and funding to organize (Martone, Garcia-Castro, & VandenBos, 2018). Interview conducted also confirmed to me that academics are having concerns in sharing data because it requires extra effort. Therefore, the following hypothesis was postulated.

H8: Effort expectancy negatively influence data sharing practices in the academic environment.

ix. Expected Rewards

Researchers' anticipation of the benefits as a result of data sharing would positively determine their data sharing practices. Whenever there is low or sometime no benefits these scholars are unlikely to share their data with colleagues. Most of the academics consider having series of citations and credits normally increase their academic recognition. Several studies demonstrated anticipated benefits as one of the determining factors for research data sharing. Researchers view data sharing as providing opportunities for academic compensations by way of citation and authorship that can develop their academic career (Kim and Adler, 2015). The ability to get commendations through various means like email and other social networks on the data shared by researchers also influence positively the attitudes of such researchers regarding their data sharing practices (Schmidt, Philipsen, Themann, & Ziefle, 2016). My interview established that academics are eager to give out their data particularly if they anticipate benefits from such exercise. Therefore, the following hypothesis was postulated.

H9: Expected Rewards positively influence data sharing practices in the academic environment.

x. Legitimate Concern

Previous studies indicated that academics legitimate concern as an important factor and a barrier that determine and negatively affect their data sharing practices. Data sharing become concern and put doubt in the mind of academics whether to involve in sharing or not. Based on the interview conducted, concern on the possibility of been unable to regulate over your data, missing publication chances, being hurting by peers which they negatively determine how academics could share their data. Legitimate concern involves in data sharing potentially have negative impact on researchers' career (Fortunato, Grainger, & Abou-El-Enein, 2018). Different researches from various disciplines have identified legitimate concern in data sharing to be one of the reasons why some researchers stay away and decide not to participate in sharing with some investigators (Higgins & Green, 2018). Consequently, if researchers are certain that data sharing has likely negative consequences for their professions, they may not participate. Therefore, the following hypothesis was postulated.

H10: Legitimate concerns negatively influence data sharing practices in the academic environment.

xi. Beneficence

It is the basis for some generally acceptable actions that involved volunteering donation for that, data sharing should be driven by the altruistic purpose of promoting research in academic community. Some studies in the past also demonstrated link between altruism and research data sharing and finally discovered that it is a significant factor influencing data sharing practices within the researchers (Fecher, Friesike, and Hebing, 2015; Kaye, 2012). It is also believed that those scholars that voluntarily donate data to institutional repositories happened to have more altruism and thus, keep data freely available to colleagues (Kim and Stanton, 2012). Similarly, in 2013, a research on national survey was piloted by Kim's research team that involved more than 1,000 scholars in 43 different fields of studies revealed at the end that researchers' altruism is really connected positively with among of data researchers shared (Kim and Stanton, 2013). Interview conducted also confirm researchers are always willing to make data freely available to their colleagues. For that reason, the following hypothesis was postulated.

H11: ***Beneficence*** positively influence data sharing practices in the academic environment.

xii. Community Culture

The beliefs and tradition in an environment normal influence the behavior of people in that area. In an academic organization, sharing is considered an important feature of scholarly collaboration. Thus, can influence data sharing practices among stakeholders. Out of all the materials to be shared, research data is seen as a cherished basis since it permits researchers to create differences in virtually all areas of development (Corti et al., 2019). Data sharing belief in some organizations is encouraging but most of the institutions are unconvinced in making research data freely available to public. Thus, community belief raised a lot of logical as well as sociological concerns (Mennes et al., 2013). My interview established that the culture of academics' community influence how they share their data. Therefore, the following hypothesis was postulated.

H12: Community culture negatively influence data sharing practices in the academic environment.

xiii. Discipline Norms

Generally speaking, some scholars have expressed their views on how discipline norms influence researchers' data sharing. For instance, Kim, 2013, stated that data sharing is not uniform rather it differs from one discipline to another. Some disciplines as norms, they considered data sharing as part of their professional responsibility and are expected to value and involve deeply in data sharing practices most as they feel pressure from their colleagues to share data (Kim and Stanton, 2012). Other researchers have the belief that those constantly shared data usually improve their research performance (Kim and Stanton, 2012). Therefore, the following hypothesis was postulated.

H13: Altruism positively influence data sharing practices in the academic environment.

3.5.3 Instrument Development

The instrument was molded based on the theory of organizational culture (TOC). This theory has been described as a complex entity of values, beliefs, behavior norms, and practices shared by personnel within an establishment (Hoogervorst et al., 2004). Theory of organizational culture was categorized in to three layers (artefacts, espoused belief and values and basic underlying assumptions). This has properly incorporated the thirteen constructs found in the research which are divided in to organizational, personal and social attributes. Some of these constructs are generated from the interview and others are from the literature.

A comprehensive review of literature was complemented to recognize and assess the prevailing measurement items appropriate to every identified construct. Nevertheless, fresh measurement items were created from the interview as interview respondents revealed infrastructure and community culture as some of the new constructs.

Table 3.1: Hypothesis Development

Constructs	Hypotheses	References
Organizational attributes		
Organizational structure	There is significant relationship between organizational structure and data sharing among academics	Schein,1990, Mulder, 2013
Infrastructure	There is significant relationship between infrastructure and data sharing among academics	Interview
Data repository	There is significant relationship between data repository and data sharing among academics.	Tenopir, et al., 2011
Research funders	There is significant relationship between research funders and data sharing among academics.	Kim, 2013, interview
Perceived pressure by Journal	There is significant relationship between perceived pressure by journal and data sharing among academics.	Kim, 2013, interview
Policy/ guidelines	There is significant relationship between policy/guidelines and data sharing among academics.	Tenopir, et al., 2011

Table 3. 1 continued

Personal attributes	Conditions for data sharing	There is significant relationship between conditions for data sharing and data sharing among academics.	Tenopir, et al., 2011
	Effort expectancy	There is significant relationship between effort expectancy and data sharing among academics.	Kim, 2013, interview
	Expected rewards	There is significant relationship between expected rewards and data sharing among academics.	Kim, 2013, interview
	Legitimate concerns	There is significant relationship between legitimate7 concern and data sharing among academics.	Kim, 2013, interview
	Beneficence	There is significant relationship between beneficence and data sharing among academics.	Tenopir, et al., 2011, interview
Social attributes	Community culture	There is significant relationship between community culture and data sharing among academics.	Interview
	Discipline Norms	There is significant relationship between discipline norms and data sharing among academics.	Kim, 2013.

Thus, this closing out the gaps that may exist between the current measurement items and the constructs studied in this research. For further clarification, the theory, description of respective constructs, conceptual definition, operational definitions references and the interview are clearly presented in the table below.

i. Instrument Testing

Here, a pilot study was conducted to test the appropriateness of the scale used, this is done through a well representative sample from the entire population. The primary intention of this preliminary assessment was to make sure that the different scales used prove the suitable level of consistency (Moore & Benbasat, 1991). Meanwhile, this research's survey instrument uses numerous measurement items, reliability of the survey items become necessary. Another purpose of this pilot test was to assist the researcher to understand clearly how researchers perceived the concept of data sharing before the actual survey.

3.5.4 Population and Sampling Technique

In the current study, the population is defined according to the purpose of the study. It is described as *"the large group of interest from which a sample is selected"*. The sample is a subcategory of persons designed out of the entire populace. It can be any size and that it will have at least one out of many characteristics which made it distinct from another population of which the researchers hope to generalize the results (Fraenkel & Wallen, 2000). The use of survey questionnaire is essential, because survey is quick, cheap and well-organized to be managed and controlled.

Survey questionnaire is a dependable instrument for determining the collected data about the samples allowing the investigator to reach at a decision on to generalize the findings from a sample of responses to the entire population. The sample of the questionnaire was attached in appendix C.

A sample frame for this study is constructed from the population that **c**omprises lecturers of the survey universities in the Northeast Nigeria. The universities are; Abubakar Tafawa Balewa University (ATBU); Maddibbo Adama University of Technology (MAUTECH); Federal University Kashere (FUK); Federal University Wukari (FUW) and Federal University Yobe (FUY). The total population of the universities involved in this research are ATBU - 2098; MAUTECH- 2231; FUK - 1023; FUW - 1106 and FUY – 1003. So the total population of this study is **7561** while the sample is 364 according Krezie and Morgan table of determining sample size in a given population which is attached in appendix D. Lecturers are indiscriminately chosen from diverse faculties based on the available scholars in the universities under study. The table below shows the total population of this study.

Table 3.2: **Population of the survey respondents**

University	Population
Abubakar Tafawa Balewa University (ATBU)	101 (27%)
Moddibbo Adama University of Technology (MAUTECH)	107 (28.6%)
Federal University Kashere (FUK)	56 (14.5%)
Federal University Wukari (FUW)	60 (15.5%)
Federal University Yobe (FUY).	54 (14.4%)
Total	**378 (100%)**

Using a statistical table that regulate how a sample size would be drawn from an agreed population, (Krejcie and Morgan, 1970) recommended that sampling of 364 is needed from any population that fall in between 7000 to 7999. Even though, current study has oversampled an additional of 14 samples to the required sampling size and a total of 378 academics were sampled. Though it is normal, the oversample to the overall sample size was done for various reasons, that include; to increase the reliability, to decrease the margin of error of the statistical result, and to address the non-responsiveness (Kotrlik & Higgins, 2001). Two criteria are taken into consideration by many researchers when selecting the sampling respondents; there are; time and cost, and accuracy as suggested by (Neuman & Kreuger, 2003).

Proportionate stratified sampling technique was used to determine the number of questionnaire to be disseminated for each university.

Abubakar Tafawa Balewa University (ATBU) Bauchi: 2098/7561 x 364 =101 (27%), Modibbo Adama University of Technology (MAUTECH): 2231/7561 x 364 = 107 (28.6%).

Federal University Kashere (FUK) Gombe: 1023/7561 x 364 = 49 (14.5%).

Federal University Wukari (FUW) Taraba:1106/7561 x 364 = 53 (15.5%) and

Federal University Yobe (FUY) Damaturu: 1003/7561 x 364 = 48 (14.4%).

Table 3.3: Instrument Development

Theory of organizational culture		Constructs	Definitions	Question Items	References	Interview
Artefacts ⇨	Organizational	Organizational structure	The normal hierarchical procedure of lines of leadership and authority of an organization	* The organizational structures create barriers in data sharing * The organizational structure facilitates data sharing process * The organization I work with stresses extent of rules/ regulations/standard procedure for data sharing * There is considerable decision by top management regarding data sharing	Schein,1990, Mulder, 2013	
		Infrastructure	Basic systems and services that an organization needs in order to function properly.	**The organization/ research project I work with:** * has better resources for training researchers on data sharing * provides the necessary platforms to support data sharing * has heterogeneous data sharing platforms * has ensure adequate facilities available (example, internet & electricity) * provides the necessary technical support for data sharing * provides necessary fund to support data sharing		Interview
		Data repository	An initiative aims at storing data for an analytical or reporting purpose.	* Researchers can easily access data repositories * Data repositories are available for researchers to share data * Researchers consider data repositories necessary for sharing data * The researchers can easily access the metadata * Metadata are available for researchers to share data	Tenopir, et al., (2011)	
		Research funders	Funders which pressurized researchers to participate in data sharing practices.	* Data sharing is mandated by the policy of public research funders * Data sharing policy of public research funders is enforced * Public research funders require researchers to share data * Public research funders can penalize researchers if they do not share data	Kim, (2013)	Interview

		Perceived pressure by journal	Journals which regulate and pressurized researchers to participate in data sharing practices.	* Data sharing is mandated by journals' policy * Data sharing policy of journal is enforced * Journal require researchers to share data * Journal can penalize researchers if they do not share data	Kim, (2013)	Interview
		Policy/ guidelines	Instructions given with the aim of strengthening and sanitizing data sharing processes.	**The organization/ research project I work with:** * has a flexible policy/ guidelines towards data sharing * has an established policy/guidelines on the data copyright/ intellectual property rights * has an established policy on the data management * has an established policy on the access control of shared data	Tenopir, et al., 2011	Interview
Espoused belief and values	Personal attributes	Conditions for data sharing	Rules pleased by researchers before agreeing to share their data	**In my discipline:** * I would use other researchers' datasets if their datasets were easily accessible * I would be willing to place at least some of the data into a central data repository with no restrictions * I would be willing to place all of my data into central data repository with no restrictions * I would be more likely to make my data available if I could place conditions on access * I would be willing to share data across a broad group of researchers who use data in different ways * It is important that my data are cited when used by other researchers * It is appropriate to create new datasets from shared data	Tenopir, et al., 2011	
		Effort expectancy	Researchers' believes that successful data sharing would demand extra energy	* Sharing data involves too much time for me (e.g., to organize/annotate) * I need to make a significant effort to share data * I would find data sharing difficult to do * Overall, data sharing requires a significant amount of time and effort	Kim, (2013)	Interview
		Expected rewards	This is a process where the researcher feels	* Data sharing would enhance academic recognition * Data sharing would improve my status in a research community	Kim, (2013)	Interview

			that data sharing could provide rewards like reputation and recognition.	* Data sharing would be helpful in my academic career e.g. more citation * Sharing research data leads to new collaboration between data users and data creators * Sharing research data increases the impact and visibility of research		
		Legitimate Concern	Potential uncertain and negative outcomes in the process of sharing data.	* There is a high probability of losing publication opportunities if I share data * Data sharing may cause my research ideas to be illegally used by other researchers * The data shared may be misinterpreted by other researchers * I believe that the overall risk of data sharing is high	Kim, (2013)	Interview
		Beneficence	A strong desire to help others through data sharing	* I would share research data to promote innovation by potential new data uses * I would share research data to encourage scientific enquiry * I would share research data to encourage the improvementand validation of research methods * I would share research data to enable scrutiny of research findings * I would share research data to provide important resources for education and training	Tenopir, et al., (2011)	
Basic underlying assumptions	Social attributes	Community culture	Way of doing things in a given organization which monitor employee's activities	**In my community:** * the public expects researchers to actively contribute in data sharing * the public stresses the importance of data sharing to the development of organization * the culture of the community encourages data sharing * the culture of the organization provides opportunity for data sharing		Interview
		Disciplinary norms	Strategies by academic disciplines to data sharing	* researchers care a great deal about data sharing * researchers share data even if not required by policies * many researchers are participating in data sharing * it is expected that researchers would share data	Kim, 2013.	

3.5.5 Administration of the Survey

For administrating the survey instrument, the researcher considers the population of the respective universities using stratified sampling techniques to identify the sample for each university. As described above, Madibbo Adama University which has the highest number of academics got the lion share of 120 questionnaires with 107 returned questionnaires. Followed by Abubakar Tafawa Balewa University Bauchi that was given 115 questionnaires (101 returned questionnaires). Then Federal University Kashere with allocated 65 questionnaires (56 returned questionnaires) Federal Universities Wukari has 70 (60 returned questionnaire) and Federal University Yobe got 65 with 54 returned questionnaires. In totally, 440 questionnaires were distributed, and 378 respondents returned their questionnaires. This gave the researcher the sum for 86.3% as a response rate and is quite appreciable owing to the following reasons:

1. The researcher took his time to involve personally in the distribution of the questionnaire to the respondents in their various faculties.

2. There was also persistent follow up through contacting the respondents from time to time.

3. Again, the researcher himself received the filled questionnaire and requested some the respondents to fill some unfilled areas in the questionnaire.

Familiarity of the researchers with some of the respondents helps in answering the questionnaire.

Table 3.4: Number of Questionnaire Distributed for each University

University	No. of Questionnaire Distributed	No. of Questionnaire Returned
Abubakar Tafawa Balewa University (ATBU)	115	101
Moddibbo Adama University of Technology (MAUTECH)	120	107
Federal University Kashere (FUW)	70	60
Federal University Wukari (FUK)	65	56
Federal University Yobe (FUY).	65	54
Total	**440**	**378**

i. Consent Letter

The researcher has personally visited all the universities under study and was courteously received by the proposed participants. The researcher explained clearly the purpose of the proposed research. Most of the participants also insisted to see a copy of the consent letter before allowing the interview to be conducted. For the participant to be assured that their names and that of their universities shall whatsoever not appear in the final report (The consent letter is attached in appendix B). Again, for the purpose of confidentiality of information of the participants, codes were used instead of individual's real names of rank. Similarly, most of the participants also insisted to see a copy of the consent form before allowing the interview to be conducted.

3.6 Data Analysis

Data collected and research framework can be analyzed by using either the traditional method using the regression or by structural equation modelling which is more popular nowadays. But it has been emphasized that the decision of using which analysis technique depends solely on some of the assumption. The assumptions depend normally on research model and structure and for this study, the both the research model and structure are considered very simple as they are straight forward. All the latent variables are seen to be observable and measure without error. In this study, the second-generation technology would be used by means of running the research model via SEM (PLS). Because second generation techniques especially SEM permits researchers to response to a group of organized research questions in a systematic, single and comprehensive analysis by modelling the relationship between several independent and dependent construct concurrently (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017). The SEM is used to test the information system research meets for high quality statistical analysis.

SEM is the mixture of both factor analysis and multiple regressions which comprises a sequence of statistical methods that permit multifaceted relationships between one or more independent variables and one or more dependent variables. SEM can perfectly be used to response to any research question concerning either indirect or direct observation of one or more independent variables or one or more dependent variables. Nevertheless, the main goal of SEM is to regulate and validity a proposed causal process and/or model. Consequently, SEM is a confirmatory technique. The structural equation modeling process forms around two steps: 1 for validating the measurement model and 2 befitting the structural model. An organized presentation of these principles trails a two-step procedure as revealed in Table (3.5). The former is accomplished primarily through confirmatory factor analysis, while the latter is accomplished primarily through path analysis with latent variables.

Table 3.5: PLS-SEM

Logical Assessment of PLS-SEM	
Assessment of the Measurement Models	Internal consistency (composite reliability) indicator reliability convergent validity (average variance extracted) Discriminant validity
Evaluation of the Structural Model	Coefficients of determination (R^2) Predictive relevance (Q2) Size and significance of path coefficient f2 effect sizes

i. Data Preparation

The concept of data preparation is similar to analysis methods. For research engaging PLS-SEM, (Hair et al. 2014) address various aspects with the aim to scrutinize and to guarantee that data is satisfactory to PLS-SEM analysis standards. "PLS-SEM is seen extremely strong when the missing values are lesser than an attainable level" (Hair et al., 2014). So the initial validation is to recognize missing data and eliminate comments that surpass 15% of incompleteness. From the 378 total cases in the dataset, no case was incomplete this was possible since the researcher personally involved in every bit of the distribution of the survey instrument to the participants. The total case conformed with the 85% of completeness suggested by (Hair et al. 2014), with proper checking by the researcher, no single case was found incomplete in the survey. Considering the total usable cases, this research has not experienced any missing values

An additional recommendation is to eliminate any doubtful response patterns comprising straight lining and outliers (Hair et al., 2014). In the case of straight lining reveals cases where participants tick the same response for a high proportion of the questions, while outliers are extreme responses which can provide misrepresentation in statistics. The dataset was checked for straight lining, and no such cases were met. Outliers was also being computed directly on Smart-PLS while running the main data analysis. Each of these cases was cautiously inspected, but no case was detached for the concluding analysis because they had rational scores for each variable. The outlier can be seen in further section.

As a known fact, PLS-SEM stands a non-parametric technique and consequently, does not need particular assumptions about the distributional features of the data to offer accurate results. Although it is an easy modeling technique with impartially free assumptions to data and that need little about normality, the researcher found it desirable to confirm if data is not too far abnormal, which may bring problems in parameters' significance assessment (Hair et al., 2014). Thus, normality test was done.

Normality of data is usually measured by certain statistical approaches by means of Kurtosis and Skewness test and the Kolmogorov and Shapiro technique (Hair, Sarstedt, Ringle, & Gudergan, 2017). In the particular study, the normality test was considered to be the main assumption which signify the results of normality test involving the entire items in the model. The result therefore showed that the skew and kurtosis of all items were laid between ±2 for skewness and ±7 for kurtosis respectively. Then, it can be resolved that the data set of all items were well-modelled by a normal distribution. The skew ranged from -1.341 to 0.942 and the kurtosis ranged from -1.21 to 1.245, as described in Table 5.5.

ii Data Editing and Cleaning

Prior to data analysis the research data need to undergo editing and cleaning process. These process are major steps for data analysis-readiness, and for permitting to spot potential anomalies in the dataset, and ease them, this can guarantee that the data is valid.

The final survey data was firstly exported to an Excel spreadsheet for variables recoding and for the dataset codebook creation. At this step, after a first screening of the observations in which no case was detached because all respondents showed in open comment boxes that they were all academics and hence were inevitably targeted sample of interest of this research.

Moreover, bearing in mind the demographic variable of the respondents, all cases were included as they all belong to the targeted participants as they are all identified as academic staff. This verdict was made considering that data sharing practices among academics are the same in respective of their disciplines. The respondents were drawn from diverse faculties ranging from education, engineering sciences, social science and others. The researcher with the help of his friends was able to edit and clear the research data and make sure only the targeted respondents were involved in the survey.

Since this research used a manual survey involving friends as assistance, errors of data entry were reduced. However, an initial checking of correspondence between responses when the data report was exported to Excel and later to SPSS was still conducted to assure accuracy of the data. Individually response case was cautiously revised to reveal any contradictions in the data. This check has permitted the researcher to erase some unwanted questions particularly to demographic questions such as marital status and specialization option. In the process, one participant mentioned that he was filling boring and this took the researcher some minutes to convince the participant to proceed with the survey. Editing and cleaning dataset has helped in purifying the data before the real analysis.

iii. Response Rate

The response rate of the current study is appreciable since the respondents for the survey were allocated based on the population of the concerned universities who varied in terms of population. The university with the highest response rate is Modibbo Adamawa University of technology (MAUTECH) that got the highest number ofsamples (120) as they have the larger population of 2231 academics. Followed by Abubakar Tafawa Balewa University (ATBU) with the total population of 2098 and with sample of 115 academics. Then the remaining three universities Federal University Kashere, Federal University Wukari and Federal University Yobe based on their population got 70. 65, 65 respectively. The total number of 440 questionnaires expecting no fewer than 364 as the sample of the study. Contrary to prior expectations of the researcher who thought less questionnaires may be returned, 378 were returned and found usable. This shows the required sample is achieved with addition of 14 respondents. The total response rate of the survey participant was clearly presented in the Figure 5.1.

Table 3.6: Response Rate

University	Faculties	Total No. of Academics	Sampling Size	Respondents	Response Rate
Abubakar Tafawa Balewa University (ATBU)	5	2098	115	101	88.7%
Madibbo Adama Uni. of Tech. (MAUTECH)	5	2231	120	107	89.1%
Federal University Kashere (FUK)	4	1023	70	56	80%
Federal University Wukari (FUW)	4	1106	65	62	93.8%
Federal University Yobe (FUY)	4	1003	65	52	80%
Overall response rate 86.3%					

3.7. Pilot Study

When the questionnaire was planned, the researcher ran a pilot study to simplify the comprehending of the respondents on the questions given to them. Thus, the pilot study was conducted to find the flaw before the actual survey is conducted with the actual sample. The main purpose of undertaken this pilot test was to make sure that "the various scales prove the suitable level of reliability. A total of 60 responses were gathered from Nigerian's academics who studied in Malaysia. The researcher sent the survey instruments to experts for comments and validation. Three of these experts are from university of Malaya while two are from Nigerian universities (Abubakar Tafawa Balewa University and Bayero University Kano). The researcher's supervisor also helps in preparing the pre-testing by observing some corrections and suggestions.

A pilot study is considered indispensable as it would help in identifying some lapses to ensure corrective steps are taken to evade any form of irregularities or misapprehensions before getting into the real survey. During the pilot study procedure, the researcher was able to identify whether the questions were suitable to be asked or not. (Oppenheim, 1992) stated that through pilot study, the researcher can check the wording of the questions and, where necessary, to improve the questions. Pilot study permits the researcher to create changes or revisions to the instruments before the survey is carried out. In-depth review of all instruments with insightful comments and editing was done by the researcher's supervisor. After the pilot study, little changes were observed from the participants' responses where all the participants' observations, comments and corrections were affected.

i Content Validity by Expert

At this stage, a panel of expert from the department of library and information **science** that validated and reviewed the survey instrument. The aims of this exercise involve firstly, the assessment of the construct validity of the items at hand and secondly, modification of vague items after the early item's creation Moore & Benbasat, (1991). The survey instrument needs to be understood by all the respondents to reduce inadvertent mistakes. The panel of experts was comprised of five (5) experienced lecturers in the field of library and information science. They were provided with the objectives of the present research which guided them in providing well assessment. They validated the survey instrument based on introductory instruction, overall questions clarity, structure and format adequacy, sentence structure, adequate and clear instruction. Therefore, the feedback from the panel of experts was employed to increase the lucidity, suitability and relevancy of the survey instrument. Based on the comments and suggestions of the panel of experts, the researcher detached and amended some of the items which are found unsuitable.

ii. Construct Validity

Construct validity is used to determine how well a test measured what it is supposed to measure. The results of the pilot test indicated that, the fourteen constructs provided in the survey questions (all items) were verified for reliability, by means of Cronbach's alpha (Table 3.7). There certain approaches to construct validation: internal consistency, convergent validity and discriminant validity. Convergent validity means the amount to which one measure of a concept is similar to other measures of the same concept (Schutt, 2009).

a. **Discriminant Validity**

Discriminant validity means the amount to which a measure of a concept is different from other measures of other concepts (Henseler, Ringle, & Sarstedt, 2015). This can be described as a situation when a construct is really not similar from other constructs by empirical standards. Subsequently, discriminant validity suggests that a construct is unique and captures phenomena not described by other constructs in the model. A construct must have adequate discriminant validity if the squared AVE exceeds the correlation among the constructs (Fornell and Larcker, 1981). This study has tried to show the correlation of latent variables and discriminant validity based on Fornell- Larcker which shows the discriminant validity is adequate for all of the constructs.

b. Convergent Validity

In a simple term, convergent validity means the situation where two measures of constructs that theoretically should be related are actually related. Is to assess a measure associate positively with other measures of the same construct. For the purpose of this pilot study, Cronbach's alpha is used in measuring convergent validity of the constructs and the results is higher than 0.7 which is suitable. This study has the most suitable that range in between 0.83 and 0.96 Therefore, the findings demonstrate that convergent validity occur for the constructs of this study.

iii. Internal Consistency Reliability

Internal consistency measures whether several items that propose to measure the same general construct produce similar scores. The most popular method for measuring the internal consistency is Cronbach's alpha, which gives an estimate of the reliability based on the inter-correlations of the observed indicator variables but it is sensitive to the number of items in the scale and lead to underestimate the internal consistency reliability. The internal consistency analysis using Cronbach's alpha are resulted all dimensions *are* accepted at a score from 0.831 to 0.935 which exceed the cut-off point of >.07 Cronbach's Alpha.

Table 3.7: Cronbach's Reliability Test (N=60)

Construct	**No of items**	**Cronbach's alpha**	**Cronbach's alpha based on standardized items**
Discipline norms	4	.832	.848
Research funders	4	.922	.920
Perceived pressure by Journal	4	.892	.905
Data repository	5	.891	.891
Effort expectancy	5	.897	.901
Legitimate concern	4	.933	.934
Beneficence	5	.908	.919
Conditions for data sharing	7	.920	.920
Organizational structure	4	.955	.956
Community culture	4	.961	.962
Infrastructure	6	.903	.913
Policy/guidelines	4	.928	.930
Expected rewards	4	.928	.930
Data sharing practices	4	.867	.861

Construct 1 (discipline norm) showed a high internal consistency with an overall Cronbach's alpha of .8.32. Item statistics (mean and SD) are at least moderate. Inter-item correlation all is very good while the summary item statistics was moderately explained throughout. Overall, there has been a very good reliability and no item was removed. This level of internal consistency was also seen for the remaining constructs (constructs 1-14). Construct 2 (Research funders; Cronbach's alpha = .922), construct 3 (Perceived pressure by journal = Cronbach's alpha = 892), construct 4 (Data repository = 891), construct 5 (Effort expectancy = 897), construct 6 = (legitimate concern = 933), construct 7

(Beneficence = 908), construct 8 (conditions for data sharing = 920), construct 9 (organizational structure = 955), constructs 10 (organizational culture = 961), construct 11 (infrastructure = 903), construct 12 (policy/guidelines = 928), construct 13 (Expected rewards = 928) and construct 14 (data sharing practices = 867). Looking at the entire results, internal consistency for the tenth construct (Community culture) was very good showing high Cronbach's alpha (.961). The results have been summarized in the table 3.7.

3.8 Summary

This chapter has explained the research paradigm and presented the method and research design applied in this study. Based on the relevant literature review on research data sharing has directed that a survey method is appropriate even an interview is needed for research question to explore the perception of research data sharing. The study is conducted in two phases, the first being an exploratory interview phase to examine the perceptions of research data sharing among academics and the second phase is the survey phase to investigate the factors that influence research data sharing and the differences of research data sharing within disciplines. The framework is based on theory of organizational culture guided by (Schein, 1990). Equally, detailed procedures for pilot study and challenge during data collection are accurately described. Furthermore, the principled features like reliability and validity in quantitative and trustworthiness for interview also outlined. Analysis is done using open coding and theme coding for the interview to analysis the perceptions of academic towards research data sharing and smart PLS to analysis the factors that influence research data sharing and the differences among different fields of studies. The research design in terms of sampling size, selection of appropriate instruments, and procedure for data collection, data analysis and the challenge during data collection has been thoroughly explained to finest address the research objectives and to answer the research question.

CHAPTER 4: PERCEPTIONS OF ACADEMICS ON RESEARCH DATA SHARING

4.1 Overview

Indication has arisen from diverse disciplines that researches are not reproducible. This sign has steered to assertions among investigators that research is facing a "reproducibility crisis" (Sayre & Riegelman, 2018). A rising number of funding organizations, government agencies, and publishers are ratifying the call for improved data sharing, particularly within the researchers." Research data are a valuable resource that has significant value beyond its use in the original research. Several funding bodies and other related institutions encourage data sharing as it increases transparency and improves the accuracy of research (Olson & Downey, 2016). To decide on how and when to share data squarely depends on the scholars' perceptions of the term "research data sharing". To find the perception of academics on data sharing an interview was conducted.

The interviews were conducted with 22 academics from 22 faculties within the five universities under study targeting to addressing the following research objectives; (i) how does Nigerian academic community perceive data sharing? (ii) what are the motivations of research data sharing to academics? and (iii) what are the perceived risks for academics in sharing their research data? These interviews offer more in-depth information on the academics' views on their research data sharing, their awareness, understanding and their familiarity motivations and risks of research data sharing practices. The results of the interviews became useful in developing the survey instrument.

4.2 Information of Participants

The total number of academics interviewed was 22, comprising 4 females (18.18%) and 18 males (81.81%). The participants derived from five universities; 5 respondents from Abubakar Tafawa Balewa University (ATBU) and Modibbo Adamawa University of Technology Yola (MAUTECH) respectively. 4 respondents from Federal University Kashere; Federal University Wukari and Federal University Yobe accordantly. These respondents represent the variety of disciplines and positions in the universities that is (from assistant lecturer to professors) to best symbolize the broad research data sharing practices of these academics. The frequency analysis indicated that 18 (81.81%) of the respondents were male and female were just 4 (18.18%).

There were five universities involved in the interview they are; Abubakar Tafawa Balewa University (ATBU) has 5 respondents (22.73%). Modibbo Adama University of technology (MAUTECH) has 5 (22.73%). Federal university Yobe, Federal university Kashere (FUK) and Federal University Wukari haves 4 (18.18%) each. This result showed that ATBU and MAUTECH have more respondents with 5 respondents each more than other three universities who were having 4 each this happened as a result of the population of the first two universities are bigger than the last three ones. The result of the area of specialization showed that the highest percentage belonged to the Engineering with 4 respondents (18.18%) followed by education and agricultural that have 3 respondents (13.62%) each. Sociology and biology have 2 respondents (9.8%) each; while the remaining disciplines (Banking and finance, physics, geology, medicine, accounting, political science, mathematics and computer science) have single representative (4.54%) respectively. Table 4.1 delivers the demographic profile of the interview participants which revealed the participant's age, gender, academic position, their various universities and field of studies.

Table 4.1: **Demographic Information of the Interview Participants**

Participants	Age	Gender	Academic Position	University	Field of studies
DN1	56 years	M	Prof.	ATBU Bauchi	Education.
DN2	52 years	M	Prof.	ATBU Bauchi	Geology
DN3	54 years	M	Ass. Prof.	ATBU Bauchi	Engineering
DN4	57 years	M	Prof.	ATBU Bauchi	Agriculture
DN5	54 years	F	Dr.	ATBU Bauchi	Accounting
DN6	44years	M	Prof.	Mautech Yola	Agriculture
DN7	48years	M	Prof.	Mautech Yola	Education
DN8	41years	M	Ass. Prof.	Mautech Yola	Medicine
DN9	50years	F	Prof.	Mautech Yola	Physics
DN10	51 years	M	Prof.	Mautech Yola	Engineering
DN11	43years	M	Dr.	FUG, Yobe	Agriculture
DN12	51years	M	Prof.	FUG, Yobe	Biology
DN13	42years	M	Ass. Prof.	FUG, Yobe	Sociology
DN14	46 years	M	Prof	FUG, Yobe	Education
DN15	43 years	F	Prof.	FUK, Gombe	Banking and Finance
DN16	50 years	M	Prof.	FUK, Gombe	Biology
DN17	52 years	M	Ass. Prof.	FUK, Gombe	Political science
DN18	49 years	M	Ass. Prof.	FUK, Gombe	Engineering
DN19	41 years	M	Prof.	FUW, Taraba	Sociology
DN20	49 years	M	Dr.	FUW, Taraba	Mathematics
DN21	51 years	M	Prof.	FUW, Taraba	Engineering
DN22	55 years	F	Prof.	FUW, Taraba	Computer science

The highest number of the participants are from Abubakar Tafawa Balewa Bauchi (ATBU) and Modibbo Adama University of technology (MAUTECH) with 5 participants from five faculties each since they have the highest number of academics than the rest. However, all the remaining three universities were adequately represented with the each of them having 4 participants. This is because the population of the academics in the last three universities are less than that of the first two.

4.3 Findings

It pertinent to briefly discuss the data of this research. The data of this research was generated from both interview and survey instrument (questionnaire). Data from interview involved the perceptions of the academics towards data sharing (RQ1), then the motivations of data sharing among academics (RQ2) and finally the perceived risks (RQ3) involved in data sharing. Data from survey instrument comprises the personal attributes (RQ4), organizational attributes (RQ5) and social attributes (RQ6) and the differences in data sharing between social sciences and sciences scholars (RQ7). The following are the interview results of this research covered research questions 1, 2 and 3.

4.3.1 RQ1: How does Nigerian academic community perceive data sharing?

RQ1 was addressed using interview, its objective was as follows; to examine the perceptions of research data sharing among academics in Nigeria. One of the questions queried in the interview was how Nigerian academics perceives data sharing. Series of responses were gathered from the respondents that include seeing data sharing as a useful event and with few seeing it as nothing good. Table 4.1 indicated that participants become awareness, understanding and familiarity with data sharing through various channels.

Awareness: It is the ability to rightly know and perceive, to sense, to be mindful of events, (Eastwood & Smilek, 2005). Researchers long ago realized that they must make their data accessible in order to attain research progression although, it should be done carefully. Data sharing practices differ from one discipline to another. Some disciplines encourage data sharing more than others (discipline receptiveness), Funding agencies request researchers to make their data available to the public while some journals publishers have specific guidelines which require scholars to share their data with other investigators (Nosek et al., 2015). All these and other related influences make researchers to be fully aware of data sharing.

Most of the interview respondents started their discussion on research data sharing with comments about their awareness to research data sharing practices in the academic setting. An appearing problem appear to be the lack of infrastructure to perform data sharing without complication. Under awareness the following themes were identified. Discipline receptiveness, Funding agencies and Journal publishers.

Discipline receptiveness- Several the respondents revealed that their awareness was traced through the interest of their fields concerning research data sharing. Data sharing practices differ from one discipline to another. Some disciplines encourage data sharing more than others (discipline receptiveness) for example, Expression like: *'Our field encourage data sharing hence, we all have prior knowledge about it'* (DN2) and *'I was actually informed about data sharing through a colleague from the same discipline"* (DN7) showed the interest of disciplines on research data sharing. Upon investigation, it was found that majority of the discipline's actual moved their attention towards research data sharing. Consequently, lecturers are much more awareness of sharing research results among themselves.

Funding agencies- Similar to discipline receptiveness, majority of the respondents showed that various funding agencies made them know research data sharing and emphasized about making research data visible available. Before access any research fund most of the funding agencies demand researchers to make their data available to the public. For instance, a statement such as: *'Nowadays, most of the funding agencies required researchers to make their data publicly accessible as a condition for providing grants'* (DN11). And *'I was personally directed to fill out an agreement form showing my readiness to share data'* (DN20) indicated the influence of funding agencies on the awareness of research data sharing of the academics. By researching, it was realized that presently funding agencies laid some policies to potential researchers regarding the need to make research data freely available to public before any research fund will be issued. Hence, academics become conscious of research data sharing around them.

Journal publishers- Another subtheme found under awareness is the role of the journal publishers in alerting the academics on the existing of research data sharing. Journal publishers usually have specific guidelines which require scholars to share their data with other investigators. An example is the expressions by some of the respondents like: DN18 *'A lot of publishes ask researchers to deposit datasets in public platforms before considering their articles for publication'* (DN18) and 'Publishers inform scholars about the idea of sharing data prior to publication' (DN21) which was evidently know that currently journal publishers are with the habit of informing the scholars on the need for open access. All these and other related influences make researchers to be fully aware of data sharing. Overall, it can be seen that must of the academics nowadays are aware of research data sharing. Table 4.2 illustrates the themes, subthemes and number of respondents about research data sharing awareness;

Table 4.2: Research data sharing awareness of academics

Themes	Verbatim statements	Participants (N)
Discipline receptiveness	Our field encourage data sharing hence, we all have prior knowledge about it (DN2) I was actually informed about data sharing through a colleague from the same discipline (DN7)	DN1, DN2, DN3, DN7, DN12, and DN14, DN11, DN18, DN19, DN20 and DN21. **(11)**
Funding agencies	Nowadays, most of the funding agencies required researchers to make their data publicly accessible as a condition for providing grants (DN19) I was personally directed to fill out an agreement form showing my readiness to share data (DN11)	DN11, DN18, DN19, DN20 and DN21. **(5)**
Journal publishers	A lot of publishes a1k researchers to deposit datasets in public platforms before considering their articles for publication (DN18) I was ones informed by journal publishers about sharing my research data prior to publication (DN20)	DN3, DN7, DN12, DN18 and DN21. **(5)**

Table 4.2 shows the diverse ways academics become awareness of data sharing that include discipline deceptiveness, funding agencies and journal publishers with their descriptive examples from the interview data. Eight academics whispered they become aware of data sharing through their disciplines. While funding agencies and journal publishers are also identified to be sources of been aware of data sharing practices by academics. with both variables having five (5) participants. Having highest number of academics been aware of data sharing via disciplines may not be by surprise since

scholars associate more with their disciplines than either funding agencies or journal publishers.

Understanding: Generally, sharing data is understood differently by academics. While some researchers perceive it positively by considering it as way of collaborating with other investigators. other view it negatively. Commonly, is an act of making data available for others to use (Borgman, 2012). Having clearly understand the concept of data sharing, researchers appreciate that it provides other scholars with diverse knowledge that will enrich their research. Researchers who refuse to share data often have particular motives for doing so (Tenopir 2011).

As respondents continued to talk about the actual research data sharing having being aware, they began to pronounce repeatedly the word understanding. The most important thing about research data sharing is the understanding of the concept. To them, understanding it has made them to participate fully and hence, increased their view about research data sharing. Generally, sharing data is significant however, researchers understand it differently. While some researchers perceive it as an act of helping other and collaboration with other investigators other researchers view data sharing as creating laziness. Researchers appreciate that data sharing would provide them with diverse knowledge that will enrich their research. Researchers who refuse to share data often have particular motives for doing so (Tenopir et al., 2011). Themes emerged here are helping others, collaborations and cost and time.

Researchers that interpretation research data sharing as something useful that can improve the research competence of scholars, also can leads to collaboration and helping others. The impression of these researchers is sharing all round improved research and brings goodies to academia. *'Is an exercise aims at assisting others to involve in writing many and good researches with minimal effort of searching data'* and *Ability of the early researchers to aid the younger ones in conducting their research with relevant data* stated by one of the respondents (DN1) and (DN3) respectively. Quite a number of respondents saw it as an act of collaboration by mentioned that 'Bringing scholars to work together to ease difficulties face in the process of undertaking research' (DN20), '*Research data sharing provides sanity in research where cooperation and team work prevailed'* (DN21) was very significant to enable them relate to one another. Research data sharing is an exercise that allows the researchers to have vast knowledge by collaborating with colleagues, allows scholars to build on fellow investigators' work to achieve get results within a shortage period of time (Pampel et al., 2013). Therefore, this set of respondents considered research data sharing as a welcome development in the present academic environment that looked more of data intensive.

As interview proceeded, issues arising from actual data sharing as some few respondents saw nothing good about research data sharing rather it is costly and consumes time, it also enhances laziness and plagiarism. Many researchers are not being ready to share data with other researchers (Soranno et al., 2015). '*Giving your useful research data for others to read, understand before generate their research may lead to laziness'* this is a statement from one of the respondents (DN9) and *'Research data sharing rather helping is discouraging scholars and lead to plagiarism as some may not acknowledge their original authors'* (DN15). Other group of academics mentioned certain reasons like cost, misuse and time to be there motive for not sharing. Response like *'time and cost may not allow me to share my research data'* (DN5). Many academic scholars find it difficult to share their dataset publicly as a result perceived individual cost which include time, money reputation and chance of being scooped by fellows regarding future publications (Pitt and Tang, 2013). Misuse of data often affect data sharing among the academics, as many researchers were concern that making unanalyzed data accessible could result to inappropriate use of the data or incorrect interpretation (Bezuidenhout, 2013). Though understanding is a single theme in term of research data sharing, respondents divided in to two with different opinions. This provide evidence that data sharing is viewed differently by researchers.

Table 4.3: Understanding research data sharing of academics

Themes	Verbatim statements	Participants (N)
Helping others	Is an exercise aims at assisting others to involve in writing many and good researches with minimal effort of searching data' and Ability of the early researchers to aid the younger ones in conducting their research with relevant data (DN3).	DN1, DN2, DN3, DN7, DN10, DN12, DN18. **(7)**
Collaboration	Research data sharing provides sanity in research where cooperation and teamwork prevailed (DN19)	DN11, DN18, DN19, DN20, and DN21, (**5**)
Cost and Time	Giving your useful research data for others to read, understand before generating their research may lead to laziness (DN5) Time and cost may not allow me to share my research data (DN15)	DN5, DN9 and DN15. **(3)**

Table 4.3 reveals academics comprehend the term data sharing in two perspectives. While majority considered it to be a welcome development which will lead to helping others and collaboration, some see it as a negative practice that is expensive and consumes time of the academics.

Familiarity: Understanding and being conscious of data sharing made it seen as an important requirement for effective and efficient research by researchers and research funders. Researchers familiarity is determining by the kind of platform you used in strengthen these collaborations**.** Naturally, data sharing is divided into three major categories: is either from a single user accessing data from multiple platform, multiple users accessing data from a single platform, or multiple users accessing data from multiple platform (Majrashi, Hamilton, & Uitdenbogerd, 2015).

The availability of platforms could highly facilitate this practice; hence, our interview indicated few researchers used certain platforms for accessing and sharing research data.

For instance, one of the participants was using “Gift-Cloud” platform which is a safe data platform that simplifies how researchers share data especially for medical imaging research. Some participants used Fig share and majority of the participants attached databases to published articles and or through personal website; online, using server-based data management system; depositing datasets in data repositories and the host of others.

In this technologically era, as researchers are dealing to themselves in research data sharing the issue of platform become unavoidable. Researchers’ familiarity is determining by the kind of platform you used in strengthen these collaborations**.** Naturally, data sharing is divided into three major categories: is either from a single user accessing data from multiple platform, multiple users accessing data from a single platform, or multiple users accessing data from multiple platform. The availability of platforms could highly facilitate this practice; hence, our interview indicated few researchers used certain platforms for accessing and sharing research data. For instance, one of the participants was using “Gift-Cloud” *‘I use Gift-Cloud platform to satisfy the sharing of imaging data from clinical to research institutions’* (DN2) and *I found it suitable to use Gift-Cloud in sharing my research data especially those data that contained images* (DN4). These respondents described Gift-Cloud as a platform which is a safe data platform that simplifies how researchers share data especially for medical imaging research.

Some participants used Fig share and majority of the participants attached databases to published articles and or through personal website; online, using server-based data management system; depositing datasets in data repositories and the host of others. These have been testified through the respondents’ statements. Example, *‘I simply use fig share to share data and other academic research outputs as it is a cost-effective software* (DN14). *‘Using fig share platform to share my data allows me to retain full control of* *data, including when to share what'* (DN21). '*I commonly share data by ascribing to available websites'* (DN4), *'To make my data accessible, I input it to any printed item* (DN7). *'I normal use my personal website to make research data readily available'* DN1. *'Because I only share data on require, it generally happens through my e-mail'* DN12 *and I do not use any platform in sharing data rather I deposit the little I have in the university data repository'* by (DN3). All these statements described the different channels used by researchers to share their data.

Table 4.4 displays the platform involved in data sharing practices of the academics. As clearly indicated, majority of the academics prefer to share their data through their various websites. In other words, it is believed that academics do share data through their personal websites with a high total of 19 participants shared the same views. This followed by those attaching their data to published articles with that made up the total of 15 participants and those using data repository, gift-cloud and figshare have 12, 3 and 1 participants respectively.

Table 4.4: Familiarity with data sharing of academics

Themes	Subthemes	Verbatim statements	Participants (N)
Platforms	Cloud source repository	I found it suitable to use Gift-Cloud in sharing my research data especially those data that contained images (DN4) I simply use fig share to share data and other academic research outputs as it is a cost-effective software (DN16)	DN2, DN4, DN12. **(3)** DN16 **(1)**
	Personal website	I commonly share data by ascribing to available websites (DN1) I normal use my personal website to make research data readily available (DN12)	DN3, DN4, DN6 DN8, DN10, DN11, DN12, DN13, DN14, DN16, DN17, DN18, DN20, DN21 and DN22. **(15)**
	Institutional data repository	I do not use any platform in sharing data rather I deposit the little I have in the university data repository (DN11)	DN1, DN2, DN3, DN4, DN6, DN7, DN8, DN10, DN11, DN12, DN13, DN14, DN16, DN17, DN18, DN19, DN20, DN21, and DN22. **(19)**

Today, the perception of many academics towards data sharing is changed, it is realized that researchers whether by mandatory or not, made their data obtainable with the aim to facilitate research among investigators.

4.3.2 RQ2: What motivate academics to share their data?

Although there are different definitions attached to motivation. But motivation has been defined as the process which accounts for individual's persistence, direction and intensity of effort towards reaching a goal (Velten & Lashley, 2018). Motivation is understood to be the driving force behind someone engaging any action. motivated connotes to be enthused to do something. motivated connotes to be enthused to do something. An individual is considered unmotivated when he feels no impetus, while a person who is enthusiastic toward an end is considered motivated. Why do we do the things we do? What is it that drives our behaviours?

The respondents have mentioned many things that motivated them involving in research data sharing. The respondents cited things such as looking for more citations, reciprocity, reputation, academics promotion, monetary incentives, protecting data against misconduct among others. These have been proof by their statements. For instance; *'Expecting more quotations inspire my data sharing practices'* (DN6). '*Tangible rewards such as referencing of work motivate me to open up my data to the wider community'* DN8, '*Benefiting from other scholars' data move me to share my own data' (DN7), 'My data can only be exchanged with other scholars else, I wouldn't share' (DN 12). 'I need to share data to become famous in the academic world' (DN22).*

Motivation arises from outside (extrinsic) or inside (intrinsic) the individual. While both types are essential, researchers have found them to have diverse effects on behaviours and how individuals pursue goals. For ease understanding of the effect of these types of motivation on human action, it is imperative to appreciate what each one is and how it works.

Intrinsic Motivation: Is described as an act of performing things for its inherent satisfaction (Locke & Schattke, 2018). It is the situation that an individual is motivated in doing something by internal desire. People driven by this motivation has been found to outperform other people in both in-role and extra-role behaviors (Bellé, 2013). Intrinsic motivation is considered conducive to improving individual's performance in a given organization, thus, research has been interested in studying it outcome variable (Jacobsen, Hvitved, & Andersen, 2014).

Table 4.5: **Intrinsic Motivation of Academics towards Data Sharing**

Themes	**Subthemes**	**Verbatim statements**	**Participants (N)**
Intrinsic motivation	More citations	Expecting more quotations inspire my data sharing practices **(DN6)** Tangible rewards such as referencing motivate me to open up my data for the wider community (**DN8)**	DN1, DN2, DN3, DN4, DN6, DN7, DN8, DN10, DN11, DN12, DN13, DN14, DN16, DN17, DN18, DN19, DN20, DN21, and DN22. **(19)**
	Academic promotion	Acknowledging my data by those that used can heighten by academic career via promotion **(DN4)** University that fashioned data sharing can upgrade their researchers that comply with such practices (**DN16**).	DN1, DN3, DN4, DN7, DN8, DN10, DN12, DN13, DN14, DN16, DN18, DN19, DN21. **(13)**
	Recognition	I need to share data to become famous in the academic world **(DN5**) I normally share data if it pays in the form of reputation **(DN7)**	DN1, DN2, DN3, DN4, DN6, DN7, DN8, DN10, DN12, DN13, DN14, DN16, DN17, DN18, DN19, DN20, DN21, and DN22. **(18)**

Table 4.5 shows how intrinsic motivation influence academic in their effort to share data. It is learned that more citations, academic promotion and recognitions are among the variables that affect data sharing among academics in Nigeria. Out of the total number of the interview respondents, 19 stated that expecting more citations made them to share data. While 13 and 18 respondents declared that academic promotion and recognition

among peers influence their involvement in data sharing practices respectively. By these results, it is clear that academics' data sharing is influence by expecting more citations than any other factor.

Extrinsic Motivation: has been defined as doing something as a result of been separable outcome (Locke & Schattke, 2018). Here, a person is motivated by external desire. Which means outside encouragement or rewards are earned from performing a task rather than actual enjoyment of the task. In other words, individuals are extrinsically motivated when they involve in their work for a simple reason of obtain some goal that is apart from the work itself (Kian & Yusoff, 2015). Extrinsic motivation in a simple way is when individuals are conducting behaviour for other purposes, rather than the meaning of the behaviour itself. For example, a researcher is sharing research data because the sharing will attract monetary incentives. However, the actual reason of sharing the data is to increase research progression.

Table 4.6 displays how extrinsic motivation influence academic in their effort to share data. It is belief that monetary incentives, exchange and the need to protect data against misconduct are some of the variables that affect data sharing among academics in Nigeria. Out of the total number of the interview respondents, 15 stated that protecting data against misconduct influenced them to share data. While 8 respondents declared that monetary incentives and exchange between academics influence their participation in data sharing practices respectively. Determination to protect data against misconduct was indicated to be the utmost inspiration among academics' participation in data sharing practices.

Table 4.6: Extrinsic Motivation of Academics towards Data Sharing

Themes	Subthemes	Verbatim statements	Participants (N)
Extrinsic motivation	Monetary incentives	Sometimes there is financial request before making data available to a wider range of users **(DN6)** Increased demand to access my data attracts financial incentives (DN17).	DN2, DN3, DN5, DN8, DN9, DN15, DN13, DN22. **(7)**
	Exchange	Benefiting from other scholars' data move me to share my own data **(DN5)** My data can only be exchanged with other scholars else, I wouldn't share **(DN7)**	DN3, DN6, DN8, DN12, DN14, DN16, DN19, DN21. **(8)**
	Protecting data against misconduct	RDS promotes open discussions which in turn avert research data from transgression **(DN3)** By making data open to public, scholars may not misbehave research data since is always accessible **(DN11)**	DN1, DN2, DN4, DN6, DN7, DN8, DN10, DN12, DN13, DN14, DN16, DN18, DN20, DN21, and DN22. **(15)**

Table 4.5.and 4.6 show what motivate the academics in sharing their data. Basically, both internal and external desires were found to have been motivating academics' data sharing. Intrinsic motivation involved more citations, academics promotion and recognition. While extrinsic motivation are monetary incentives, exchange and the need to protect data from misconduct.

4.3.3 RQ3: What are the perceived risks involved in academics' data sharing?

In this study, the researcher tries to describe the concept of perceived risk in data sharing and explore how academics perceive these potential risks. Most perceived risk studies in data management have been concerned with how peoples view issues related to the risk of sharing (Gewin, 2016). Perceived risk revolves around an individual's perception of how personal information could be misused in general (James, Wallace, Warkentin, Kim, & Collignon, 2017). In an interview conducted, the researcher examines the perceived risk of academics from sharing research data. Specifically, we examine (1) data privacy and (2) cultural orientation.

Data Privacy: The amount of data in academics is rapidly increasing thus, a considerable body of research has studied data privacy (Zyskind and Nathan, 2015). While there are benefits of data sharing, there is a growing concern about data privacy. Concern on data privacy is used as an indicator to examine why people should or should not participate in data sharing (Chen, Ping, Xu, and Tan, 2015).

Cultural Orientation: Culture has often associated with privacy for instance, there was arguments that culture plays an important role in developing privacy rules (F. Chen et al., 2016). Similarly, (James et al., 2017) propose that culture is an important environmental element that influences privacy perceptions. Numerous studies have incorporated culture into examinations of privacy risk in technology environments (Miltgen & Peyrat-Guillard, 2014). Consequently, current study examines the connection between perceived risk and cultural orientations which extends the exploration of culture and risk to encompass the considerations of other information. Cultural characteristics influences the ways in which individuals consider outcomes and react in situations (James et al., 2017).

Table 4.7 displays the perceived risks involved in data sharing among academics. Two themes were identified (data privacy and cultural orientation). These were followed by five (5) subthemes that were demonstrated from the participants' verbatim statements which presented the real risk perceived by academics. Lack of confidentiality in sharing data have 20 respondents which is the largest then followed by misused of data with 15, community belief 12 and mistrust and culture have 9 respondents each. Table 4.7 illustration shows that scholars are more concern about the secrecy of their data, and this may not be unconnected with the nature and sources of these data.

Table 4.7: Perceived risk of academics towards data sharing

Themes	Subthemes	Verbatim Statements	Participants (N)
Data Privacy	Confidentiality	I can share data when principles guiding data sharing are adhering **(DN2)** I don't want the secret behind my research to be revealed **(DN10**)	DN1, DN2, DN3, DN4, DN5 DN6, DN7, DN9, DN10, DN11, DN12 DN13, DN14, DN16, DN17, DN18, DN19, DN20, DN21, and DN22. **(20)**
	Misused	Fear of using illegal way to monetize my data affect how I respond to data sharing **(DN8)**	DN1, DN2, DN4, DN6, DN7, DN9, DN10, DN11, DN13, DN14, DN15 DN17, DN18, DN20, DN21, and DN22. **(16)**
	Mistrust	Some researchers may end up exposing my research weakness **(DN6)**	DN2, DN4, DN6, DN8, DN9, DN10, DN12, DN16 and DN19. **(9)**
Cultural Orientation	Community belief	I have the belief that sharing my research data can hurt my academic growth **(DN11)**	DN1, DN2, DN4, DN6, DN7, DN9, DN12, DN14, DN16, DN17, DN19, DN21. **(12)**
	Culture	The nature of our culture in this community prevents us from sharing valuable things including research data **(DN1)**	DN1, DN3, DN5, DN7, DN9, DN12, DN14, DN15 and DN20. **(9)**

Overall, the participants expressed positive perceptions regarding research data sharing among academics in Nigerian Universities. Majority of the respondents believe that data sharing if properly practiced can positively change the nature of research in universities with very few responses were yet to see the good in it.

4.4 Interview findings and Development of the Survey Instrument

The interview conducted in this study has aided in generating most of the variables found in this research. The first three research questions of this study were addressed through interview and the findings assisted in the development of the survey instrument. The first research question (RQ1) has revealed the awareness, understanding and familiarity of academics with data sharing. This question helps in providing variables such as funding agencies and journal publishers which are used in developing the survey instrument.

These variables serve as some of the ways the scholars become aware of the data sharing practices. Findings from the research questions two (RQ2) also provided anticipated benefits, infrastructure and altruism as some of the variables that motivate data sharing practices among academics. Similarly, research question three (RQ3) which chattered about risks in data sharing offered community culture, perceived effort and legitimate concerns as other variables that serve as a risk which affect data sharing practices within the academics in the Nigerian universities. Therefore, interview conducted in this study has immensely assisted in the development of the survey instrument for current research.

The subsequent mapping demonstrates how interview findings developed constructs which generated some of the survey questions. Findings from the interview provides the following constructs: Infrastructure community culture, funding agencies, journal publishers, perceived effort, anticipated benefits legitimate concerns and altruism.

Table 4.8: Mapping of Interview Findings to Survey Questions

Variables	**Interview themes**	**Survey questions**
Infrastructure	Connectivity Training Facilities	***My Organization*** * has better resources for training researchers on data sharing * provides the necessary platforms to support data sharing * has heterogonous data sharing platforms * ensured adequate facilities available (e.g. internet and electricity)
Community culture	Cultural orientation	*My community expects researchers to actively contribute in data sharing *My culture stresses the importance of data sharing to the development of institutions *The culture of the community encourages data sharing * The culture of the community provides opportunity for data sharing

Table 4.8 continued

Research funders	Awareness Familiarity	*Data sharing is mandated by the policy of public funding agencies. *data sharing policy of public funding agencies is enforced *public funding agencies require researchers to share data *public funding agencies can penalize researchers if they do not share data. **Interview and literature**
Perceived pressure by journals	Awareness Familiarity	*data sharing is mandated by journals' policy *data sharing policy of journal is enforced *journal require researchers to share data. *journal can penalize researchers if they do not share data. **Interview and literature**
Effort expectancy	Cost and Time	*I would find data sharing easy to do *I need to make a significant effort to share data *I would find data sharing difficult to do *Overall, data sharing requires a significant amount of time and effort. **Interview and literature**
Expected rewards	Motivation (Intrinsic and extrinsic)	*Data sharing would enhance academic recognition *Data sharing would improve my status in a research community *Sharing research data leads to new collaboration between data users and data creators *Sharing Research data increases the impact and visibility of research. **Interview and literature**
Legitimate concerns	Mistrust Misused Confidentiality	*There is a high probability of losing publication opportunities if I share data. *Data sharing may cause my research ideas to be illegally used by other researchers *The data I shared may be misinterpreted by other researchers *I believe the overall risk of data sharing is high. **Interview and literature**
Beneficence	Encourage collaboration Protecting data against misconduct	*I would share research data to promote innovation by potential new data users *I would share research data to encourage scientific enquiry *I would share research data to encourage the improvement and validation of research methods *I would share research data to enable scrutiny of research findings *I would share research data to provide important resources for education and training. **Interview and literature**

4.5 Summary

This chapter has offered the findings from the interview session. Together with knowledge obtained from the literature on research data sharing, particularly research data sharing perceptions, five themes and eleven sub themes emerged that form academics perceptions of research data sharing. Interview with academic revealed the urgent needs for effective data sharing within the researchers in the academic environment. Academics showed they are much aware about research data sharing; they understand both good and bad aspect of it. Their familiarity with few platforms that help in data sharing was also revealed and also what motivate them to participate. However, researchers want their research data to be protected for some of them showed their concerns about the risks and privacy of their data. Another identified issue is the scooped by peers when research data are make available. The inability of most of them to have efficient internet connection and stable power supply has also been identified as some of the problems. In generally, the five themes and eleven sub themes emerged centered around views and issues on research data sharing within the academic's environment. The next chapter presents the survey findings that were realized in this study.

CHAPTER 5: FACTORS THAT INFLUENCE DATA SHARING PRACTICES

5.1 Introduction

This current chapter concentrates on the analysis and results and of the survey responses. The demographic data of the survey participants were first presented at the beginning of this chapter. Research results of the research question four five, and six are presented using the partial least squares (PLS) method in testing the research hypotheses.

5.2 Demographic Profile of the survey participants

Participants for the main study are allocated are based on the population of the concerned universities who varied in terms of population. As earlier stated, the total number of 440 questionnaires which contained 64 questions was distributed to the identified respondents from 21st of February, 2018 to 14th March 2018. Which means three weeks' timeframe given to the participants to respond to the survey. Though, in returning the questionnaire, only 378 were returned and found usable. This shows the required sample is achieved with addition of 14 respondents.

Table 5.2 demonstrates the summary of the survey respondents' demographic profile. Survey participants profile comprises of their gender, age, year of experience, their faculty and qualification.

Table 5.1: Survey Participant's Profiles

Variable	Level	Frequency	Percentage
Gender	Male	301	79.6
	Female	77	20.4
Age	21- 35 years	17	4.5
	26- 30 years old	46	12.2
	31- 35 years old	169	44.7
	>= 40 years old	146	38.6
Experience	<= 5 years	22	5.8
	6 -10 years	78	20.6
	11-15 years	138	36.5
	16- 20 years	106	28.0
	>= 25 years	34	9.0

Table 5.1: Continued

Faculty	Education	34	9.0
	Engineering	49	13.0
	Sciences	118	31.2
	Social Sciences	163	43.1
	Others	14	3.7
Qualification	B. Sc.	8	2.1
	M. Ed.	46	12.2
	M.Sc.	220	58.2
	PhD	73	19.3
	Others	31	8.2

Table 5.2 reveals the response rate was satisfactory for the purpose of data analysis, and also indicates that to some extent a portray the sub-disciplines with most scholars in the sciences and social sciences.

5.1.1 Descriptive Analysis of the Measurement Scales

In the current study, descriptive statistics were calculated for the entire measurement scales which are divided in to three factors (institutional, social and individual factors). The calculation including the mean, standard error, standard deviation, skewness and kurtosis. By calculating means and standard deviations for each measurement variable the researcher was able to measure of spread of scores within a set of data. Skewness and kurtosis were also calculated because they offer a calculation of how much the assumption of normally distributed measurement data has been violated. Majority of the three hundred and seventy-eight (378) measurement variables unveiled substantial non-zero values for both kurtosis and negative skewness.

The next stage was to analyse and calculate raw scores of the latent variables for each survey respondent. The latent variables in the current research are reflective measures, signified by computing a mean score for each of the thirteen-measurement scale's set of survey questions. The individual survey respondent latent variable mean scores were also aggregated into overall mean scores for each latent variable in this study. The results are presented in Table 5.3 including standard error of the mean scores, standard deviations, skewness and kurtosis. All the thirteen latent variables produced t-statistic values with magnitudes larger than 2, indicating those aggregate mean score results are faultless.

The collective mean scores illustrate that the study sample populations responded positively to all questions about their discipline norms, indicating most respondents feel their discipline influence positive the level of their data sharing practices. Questions about funding agencies and journal publishers also produced consistently positive responses, well above the midpoint of each response scale. Similarly, the aggregate scores for data repository, organizational structure, infrastructure, policy/ guidelines, anticipated benefits, and altruism were also beyond the mid-point of the data sharing practices response scale. While scores from conditions for data sharing, legitimate concerns, perceived effort and community culture are significantly below the midpoint thus, influence negative the level of their data sharing practices. A complete listing of descriptive statistics of measurement scale presented in the table 5.3 based on research question 4, 5, and 6.

Table 5.2: Measurement Scale of the Constructs

Scale Item	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Personal Attributes						
Effort expectancy EE1	2.18	1.124	.897	.125	.170	.250
EE2	3.64	1.034	-.430	.125	-.469	.250
EE3	3.74	1.031	-.479	.125	-.553	.250
EE4	3.79	1.091	-.618	.125	-.415	.250
EE5	3.79	1.042	-.686	.125	.019	.250
Legitimate concerns C1	3.89	1.080	-.990	.125	.405	.250
LC2	3.89	1.090	-.970	.125	.272	.250
LC3	3.89	1.070	-1.002	.125	.444	.250
LC4	4.00	1.074	-1.092	.125	.542	.250
Beneficence BNC1	3.75	1.204	-.866	.125	-.199	.250
BNC2	3.73	1.257	-.845	.125	-.315	.250
BNC3	3.67	1.210	-.846	.125	-.233	.250
BNC4	3.72	1.198	-.767	.125	-.352	.250
BNC5	3.82	1.158	-1.014	.125	.256	.250

Table 5.2: Continued

Conditions for data sharing CFDS1	3.86	1.081	-1.057	.125	.509	.250
CFDS2	3.81	1.089	-.779	.125	-.164	.250
CFDS3	3.46	.966	-.527	.125	.128	.250
CFDS4	3.90	1.180	-.937	.125	-.048	.250
CFDS5	3.82	1.095	-.907	.125	.142	.250
CFDS6	3.77	1.032	-.832	.125	.101	.250
CFDS7	3.79	1.013	-.913	.125	.464	.250
Expected rewards ER1	2.52	.994	.388	.125	-.668	.250
ER2	2.64	1.008	.121	.125	-.906	.250
ER3	3.51	1.200	-.179	.125	-1.283	.250
ER4	3.55	1.167	-.142	.125	-1.347	.250
Organizational Attributes						
Research funders RF1	4.17	.936	-.981	.125	.072	.250
RF2	4.13	.990	-.944	.125	-.186	.250
RF3	2.62	.954	.145	.125	-.191	.250
RF4	2.45	.941	.542	.125	.126	.250
Perceived pressure by Journals JP1	3.79	1.017	-.794	.125	.179	.250
PPJ2	3.89	1.121	-1.022	.125	.337	.250
PPJ3	3.91	1.119	-.948	.125	.099	.250
PPJ4	3.90	1.069	-.997	.125	.397	.250
Data repository DR1	2.12	.976	.678	.125	-.321	.250
DR2	2.13	1.147	.789	.125	-.502	.250
DR3	2.94	1.076	.476	.125	-.757	.250
DR4	2.10	1.149	.768	.125	-.606	.250
DR5	2.15	1.192	.835	.125	-.458	.250
Organizational structure OS1	3.69	.971	-.653	.125	.211	.250
OS2	3.76	.921	-.728	.125	.649	.250
OS3	3.72	.969	-.660	.125	.264	.250
OS4	3.83	.988	-.745	.125	.193	.250
Infrastructure INF1	2.27	1.149	.939	.125	.019	.250
INF2	2.26	1.189	.898	.125	-.113	.250
INF3	2.27	1.201	.812	.125	-.353	.250
INF4	2.32	1.173	.828	.125	-.217	.250
INF5	2.32	1.152	.810	.125	-.189	.250
INF6	2.41	1.185	.858	.125	-.192	.250
Policy/guidelines PG1	2.84	.801	.024	.125	.197	.250
PG2	2.96	.777	-.141	.125	.577	.250
PG3	2.96	.826	-.044	.125	.388	.250
PG4	3.04	.781	-.112	.125	.646	.250

Table 5.2 continued

Social Attributes						
Community culture CC1	3.78	1.247	-1.019	.125	.011	.250
CC2	3.80	1.262	-.984	.125	-.077	.250
CC3	3.77	1.260	-.917	.125	-.221	.250
CC4	3.67	1.249	-.908	.125	-.257	.250
Discipline norms DN1	3.68	1.297	-.804	.125	-.492	.250
DN2	3.70	1.402	-.797	.125	-.681	.250
DN3	3.60	1.365	-.716	.125	-.731	.250
DN4	3.51	1.377	-.506	.125	-1.013	.250
Data sharing practices DSP1	2.95	.971	-.009	.125	.300	.250
DSP2	2.98	.962	-.114	.125	.138	.250
DSP3	2.93	.972	-.8008	.125	-.202	.250
DSP4	3.01	1.018	.014	.125	-.121	.250
Valid N (listwise)						

5.2 Statistical Testing of Measurement Methods

It is advisable that before running regression analysis through smart PLS researchers need to undergo different tests. These tests may include normality test, checking multicollinearity between the IVs, linearity is another assumption and other different related tests. For these reasons, the researcher of this study undergone the following tests. It is imperative to note that in some instances, the statistical analysis of the three attributes would be done simultaneously.

5.2.1 Outlier Test

Outliers offer an observation that departs significantly from other observations because of the high or low scores (Kwak & Kim, 2017). For this therefore, scholars showed that outliers can disrupt the normality (Choi, 2016). In this regard, outliers transpire while the cases have standard score greater than ±3.29 (Tabachnick & Fidell, 2001). Consequently, in this study, an outlier test is showed in table 5.4.

Table 5.3: Outlier Test

Independent variables	Minimum	Maximum
Expected rewards (ER)	-2.O27	‘2.187
Beneficence (BNC)	-2.551	1.174
Community culture (CC)	-2.428	1.097
Condition for data sharing (CFDS)	-3.135	1.226
Data repository (DR)	-1.341	2.829
Discipline norms (DN)	-2.138	1.123
Research funders (RF)	-2.519	2.266
Infrastructure (INF)	-1.286	2.645
Perceived pressure by journal (PPJ)	-3.021	1.188
Legitimate concerns (LC)	-3.016	1.121
Organizational structure (OS)	-3.350	1.526
Effort expected (EE)	-2.977	1.927
Policy/guidelines (PG)	-2.924	3.069
Dependent variables	**Minimum**	**Maximum**
Data sharing practices (DSP)	-2.284	2.364

5.2.2 Normality Test

In statistics, these tests are used to be able to know how good the data set is prepared by a standard distribution. Thus, Normality of data is usually measured by certain statistical approaches by means of Kurtosis and Skewness test and the Kolmogorov and Shapiro technique (Hair, et al., 2017). In the particular study, the normality test was considered to be the main assumption as can be seen in table 5.5 which signify the results of normality test for all items in the model. The result therefore showed that the skew and kurtosis of all items were laid between ±2 for skewness and ±7 for kurtosis respectively. Then, it can be resolved that the data set of all items were well-modelled by a normal distribution. The skew ranged from -1.341 to -0.97 and the kurtosis ranged from -0.115 to 1.245.

Table 5.4: Normality test

Independent variables	Skewness	Std. Error	Kurtosis	Std. Error
Personal Attributes				
Expected rewards (ER)	-0.033	0.125	-1.21	0.25
Beneficence (BNC)	-1.053	0.125	-0.132	0.25
Condition for data sharing (CFDS)	-1.341	0.125	1.126	0.25
Effort expected (EE)	-0.605	0.125	-0.115	0.25
Legitimate concerns (LC)	-1.27	0.125	0.913	0.25

Table 5.4: Continued

Organizational Attributes				
Research funders (RF)	-0.759	0.125	0.195	0.25
Infrastructure (INF)	-1.237	0.125	0.069	0.25
Perceived pressure by journal (PPJ)	-1.319	0.125	0.805	0.25
Organizational structure (OS)	-1.121	0.125	1.245	0.25
Data repository (DR)	0.942	0.125	-0.268	0.25
Policy/guidelines (PG)	-0.018	0.125	1.016	0.25
Social Attributes				
Community culture (CC)	-1.251	0.125	0.207	0.25
Discipline norms (DN)	-0.97	0.125	-0.486	0.25
Dependent variables	**Skewness**	**Std. Error**	**Kurtosis**	**Std. Error**
Data sharing practices (DSP)	-0.078	0.125	0.669	0.25

5.2.3 Common-Method Variance (CMV)

Because of gathering data all the model variables from single respondents in a one-time survey, common method variance might influence some postulated relations in the Smart PLS path model. To test for the potential existence of common method bias, Harman, 1976 single-factor test was used. Common-method variance (CMV) is the wrong "variance that is imputable to the measurement method rather than to the constructs the measures are assumed to represent" or equivalently as "systematic error variance shared among variables measured with and introduced as a function of the same method and/or source". An attachment of the common- method variance (CMV) can be seen in appendix E. This study applied Harman's 1976 single-factor test. The first factor accounts for only 21.596% of the overall variance, which shows that common method variance probable does not affect the results (Podsakoff, MacKenzie, & Podsakoff, 2012). Appendix D determine the CMV result based on the research study.

5.2.4 Multicollinearity and Singularity

In a simple term, multi-collinearity can be described as a situation when two or more variables are not independent. SEMs has been an influential method while using multi-collinearity in sets of predictor variables. In another word, Multi-collinearity, transpired as soon as there are very great correlations among two or more variables, which would be able to result to difficulties when performing multivariate analyses; standard errors of parameter estimates, and coefficient estimates can be affected. A correlation of more than 0.85 between variables represents high multi-collinearity (Garson, 2008). The correlation coefficients among all variables was evaluated and all the scores were less than 0.8 this results indicated there is no multi-collinearity. It is imperative to note that table 5.6. which reveals the calculation multicollinearity test based on correlation coefficients involved personal, organizational and social which are the research questions 4, 5 and 6.

i. Assessing Collinearity among the predictor Construct

A high level of collinearity is basically considered to influence the findings of analysis in two aspects. First, collinearity increases the standard errors and therefore decreases the ability to show that the estimated weights are significantly distinguished from zero. This standard is particularly problematic in PLS-SEM analysis based on smaller sample sizes when standard errors are considered to be larger because of sampling error. Second, high collinearity is expected to appear in the weights being incorrectly estimated, as well as their signs being reversed. To measure the level of collinearity, scholars have to compute the tolerance. Similarly, when there is an existence of collinearity, standard errors and variances are overblown.

5.3 Measurement Model Assessment (Outer Model Estimation)

The structural equation modeling process forms around two steps: 1 for validating the measurement model and 2 befitting the structural model. The systematic application of these criteria follows a two-step process. The former is prepared principally via confirmatory factor analysis, while the latter is established mainly by the use path analysis with latent variables. Structural equation modeling (SEM) has turn out to be a more popular particularly in marketing and management research when it comes to analyzing the cause–effect relations between latent constructs. Research exclusively appreciates

SEM's capacity to assess latent variables at the observation level (outer or measurement model) and test relationships between latent variables on the theoretical level (inner or structural model). To assess the measurement in this study, reliability (internal consistency), convergent and discriminant validity was calculated.

5.3.1 Undimensionality and Reliability

In measuring a construct with multiple indicator variable, the researcher must prove and make sure that the terms measure the same thing because lack of undimentionality is a form of measurement error. Measurement error weakens correlation and increases standard error. Several approaches exist in testing undimentionality which include Cronbach's alpha and composite reliability.

Cronbach's α coefficients and Composite reliability were calculated for the latent variables to test their internal consistency and how well these variables measure the reliability of the latent variables. As suggested by Hair et al. (2017), researchers employ Cronbach's alpha as lesser boundary and composite reliability as upper boundary to determine internal consistency. That Cronbach's alpha is 0.627 and composite reliability is 0.784. Similarly, values above 0.95 are undesirable (Hair et al. 2017).

Applying CA offers an assessment about the reliability based on indicator inter-correlations even though by PLS, internal consistency is evaluated employing composite reliability (Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018). CR for every construct in the present study ranges from 0.848 to 0.950 which is beyond the commended value of 0.7. Hence, the outcomes show that the items used in representing the constructs have adequate internal consistency reliability. As shown in Table 5.3, the items for this study had acceptable CA and CR, indicating the excellent reliability of the scales used in the study.

Table 5.5: Multi-collinearity test based on correlation coefficients

	ER	BNC	CFDS	DN	DR	DSP	RF	INF	PPJ	LC	CC	OS	EE	PG
Expected rewards (ER)	1.000	0.313	-0.353	0.248	0.253	0.623	0.229	0.295	0.315	-0.334	-0.312	0.350	-0.139	0.260
Beneficence (BNC)	0.313	1.000	-0.201	0.390	0.090	0.519	0.300	0.197	0.316	-0.131	-0.169	0.264	-0.126	0.143
Conditions for data sharing (CFDS)	-0.353	-0.201	1.000	-0.168	-0.139	-0.361	-0.090	-0.103	-0.202	0.082	0.205	-0.207	0.057	-0.086
Discipline norms (DN)	0.248	0.390	-0.168	1.000	0.047	0.525	0.294	0.259	0.390	-0.185	-0.162	0.278	-0.144	0.145
Data repository (DR)	0.253	0.090	-0.139	0.047	1.000	0.332	0.163	0.264	0.017	-0.266	-0.258	0.136	-0.144	0.118
Data sharing practices (DSP)	0.623	0.519	-0.361	0.525	0.332	1.000	0.523	0.424	0.442	-0.454	-0.428	0.444	-0.313	0.317
Research funders (RF)	0.229	0.300	-0.090	0.294	0.163	0.523	1.000	0.222	0.190	-0.186	-0.203	0.222	-0.073	0.148
Infrastructure (INF)	0.295	0.197	-0.103	0.259	0.264	0.424	0.222	1.000	0.169	-0.326	-0.235	0.113	-0.138	0.211
Perceived pressure by journal (PPJ)	0.315	0.316	-0.202	0.390	0.017	0.442	0.190	0.169	1.000	-0.131	-0.131	0.301	-0.105	0.164
Legitimate concerns (LC)	-0.334	-0.131	0.082	-0.185	-0.266	-0.454	-0.186	-0.326	-0.131	1.000	0.327	-0.092	0.310	-0.158
Community culture (CC)	-0.312	-0.169	0.205	-0.162	-0.258	-0.428	-0.203	-0.235	-0.131	0.327	1.000	-0.193	0.111	-0.245
Organizational culture (OS)	0.350	0.264	-0.207	0.278	0.136	0.444	0.222	0.113	0.301	-0.092	-0.193	1.000	-0.151	0.210
Efforts expectancy (EE)	-0.139	-0.126	0.057	-0.144	-0.144	-0.313	-0.073	-0.138	-0.105	0.310	0.111	-0.151	1.000	-0.104
Policy/guidelines (PG)	0.260	0.143	-0.086	0.145	0.118	0.317	0.148	0.211	0.164	-0.158	-0.245	0.210	-0.104	1.000

5.3.2 Reliability and Measurement Scale

This normally requires the guidelines regulatory exactly how the latent variables are measured based on the observed variables, and it defines the measurement properties of the observed variables. That is, measurement scales are concerned with the relations between observed and latent variables. Such scales specify hypotheses about the relations between a set of observed variables, such as ratings and the unobserved variables or constructs they were intended to measure. The measurement scale is significant as it provides a test for the reliability of the observed variables employed to measure the latent variables. A measurement scale that provides a poor fit to the data recommends that at least some of the observed indicator variables are unreliable and precludes the researcher from moving to the analysis of the structural model.

Assessment of reflective measurement scale includes Cronbach's alpha (CA) rho A and composite reliability (CR) to evaluate internal consistency, individual indicator reliability, and average variance extracted (AVE) to evaluate convergent validity. In the following section, the mentioned criteria for measurement scale was assessed based on reflective measurement scale.

Table 5.6: Constructs Reliability and Validity of the Measurement Scale

	Cronbach's Alpha	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
Personal Attributes				
Expected rewards (ER)	0.831	0.836	0.887	0.662
Beneficence (BNC)	0.935	0.938	0.950	0.793
Effort expectancy (EE)	0.829	0.831	0.886	0.619
Conditions for data sharing (CFDS)	0.924	0.927	0.939	0.688
Legitimate concerns (LC)	0.918	0.920	0.942	0.804

Table 5.6: Continued

Organizational Attributes				
Organizational structure (OS)	0.875	0.877	0.914	0.726
Data repository (DR)	0.915	0.922	0.937	0.748
Research funders (RF)	0.765	0.780	0.848	0.584
Perceived pressure by journal (PPJ)	0.901	0.903	0.931	0.771
Infrastructure (INF)	0.933	0.935	0.948	0.751
Policy/guidelines (PG)	0.859	0.873	0.904	0.702
Social Attributes				
Community culture (CC)	0.926	0.926	0.947	0.818
Discipline norms (DN_	0.924	0.925	0.946	0.814
Dependent Variable				
Data sharing practices (DSP)	0.901	0.901	0.931	0.770

i. Internal Consistency

The internal consistency analysis using Cronbach's alpha, rho_A and composite reliability resulted all dimensions *are* accepted at a score from 0.765 to 0.935 which exceed the cut-off point of >.07 Cronbach's Alpha, and their chart can be found in appendix F, G and H. Composite reliability (CR) is normally used in SEM for internal consistency analysis and the Composite reliability (CR) value is at acceptable (Gefen, Straub, and Boudreau, 2000) with all dimension values n > 0.70. Applying CR offers an assessment about the reliability based on indicator inter-correlations even though by PLS, internal consistency is evaluated employing composite reliability (Ali et al., 2018). While CA or CR assess related things as internal consistency, CR is focused on indicators that have different loadings. CA indicates a strict understanding of the internal consistency reliability as it does not consider equivalency among the measures and assumes that all indicators are equally weighted (Werts, Linn, and Jöreskog, 1974). A calculation of rho A was also conducted and can be found in appendix H. Therefore, Table (5.8) displays the Cronbach's Alpha, Composite Reliability of this study.

Internal consistency reliability is described as acceptable once the value is at least 0.7 at the beginning or earlier stage and values above 0.8 or 0.9 as the research progresses.

However, value with less than 0.6 reveals an absence of reliability (Nunnally and Bernstein, 1994). Table (5.8) indicates that the CR of each construct for this study ranges from 0.765 to 0.935 which is beyond the commended value of 0.7. So, the results show that the items used to represent the constructs have acceptable internal consistency reliability.

ii. Average Variance Extracted

Convergent validity involves the amount to which a particular item reflects a construct converging in comparison to items measuring different constructs (Urbach & Ahlemann, 2010). A common measure to establish convergent validity on the construct level is the average variance extracted (AVE). Using PLS, convergent validity can be evaluated using the value of average variance extracted (AVE). This principle is explained to be as the grand mean value of the squared loadings of the indicators connected with the construct (i.e., the sum of the squared loadings divided by the number of indicators). Thus, the AVE is corresponding to the commonality of a construct. According to (Fornell and Larcker, 1981), satisfactory convergent validity is attained when the AVE value of a construct is at least 0.5 and the average variance extraction (AVE) is attached in appendix I. Similarly, Table 5.8 demonstrates the average variance extracted for all the constructs.

An AVE value of 0.50 or higher indicates that, on average; the construct explains more than half of the variance of its indicators. However, an AVE of less than 0.50 indicates that, on average, more errors remain in the items than the variance enlightened by the construct (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). Table 5.9 represents constructs with AVE from 0.584 to 0.818, which surpassed the recommended value of 0.5. Therefore, the result indicates that the study's measurement model has confirmed an acceptable convergent validity.

iii. Convergent Validity

This has been described as the means to assess a measure associate positively with other measures of the same construct (Hair et al., 2014). Convergent validity can be assessed at the construct level by means of average variance extracted (AVE). This condition is labelled as the grand mean value of the squared loadings of the items associated with the construct. The most popular method for measuring the internal consistency is Cronbach's alpha, which gives an estimate of the reliability based on the inter-correlations of the observed indicator variables but it is sensitive to the number of items in the scale and lead to underestimate the internal consistency reliability. As such, it is advised to use a different measure of internal consistency reliability, which is referred to as composite reliability (CR). This kind of reliability considers the different outer loadings of the indicator variables.

Composite Reliability (CR) higher than 0.7 is suitable, and concerning our findings, this study has the most suitable CR that range in between 0.88 and 0.95. In furtherance, in this study, AVE is above 0.5 (Table 5.8). Therefore, the findings demonstrate that convergent validity (AVE) and Composite Reliability (CR) occur for the constructs of this study (Table 5.8). High outer loadings on a construct indicates that the interrelated item of each construct have considerable support with the construct. This characteristic is sometimes referring to as indicator reliability which can be calculated through outer loadings and its significance level because a significant outer loading could still be fairly weak, a common rule of thumb is that the (standardized) outer loadings should be 0.708 or higher. Indicators with very low outer loadings (below 0.40) must, however, continually be detached from the scale (Hair, Sarstedt, Ringle, and Mena, 2012). Table 5.8 shows the outer loadings of all items for all constructs in initial measurement model according to these results all outer loadings related to constructs.

Table 5.7: Result of convergent Validity

Constructs	Item	Outer loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Personal Attributes					
Expected rewards (ER)	ER1	0.852	0.831	0.885	0.662
	ER2	0.868			
	ER3	0.756			
	ER4	0.763			
Beneficence (BNC)	BNC1	0.896			
	BNC2	0.896	0.935	0.95	0.793
	BNC3	0.907			
	BNC4	0.918			
	BNC5	0.832			
Conditions for data sharing (CFDS)	CFDS1	0.808	0.924	0.939	0.688
	CFDS2	0.833			
	CFDS3	0.729			
	CFDS4	0.877			
	CFDS5	0.876			
	CFDS6	0.838			
	CFDS7	0.834			
Effort expectancy (EE)	EE1	0.535	0.829	0.88	0.6
	EE2	0.853			
	EE3	0.813			
	EE4	0.843			
	EE5	0.783			
Legitimate concerns (LC)	LC1	0.877	0.918	0.942	0.804
	LC2	0.915			
	LC3	0.923			
	LC4	0.869			
Organizational Attributes					
Data repository (DR)	DR1	0.869	0.915	0.935	0.748
	DR2	0.884			
	DR3	0.771			
	DR4	0.907			
	DR5	0.876			
Research funders (RF)	RF1	0.77	0.765	0.849	0.584
	RF2	0.795			
	RF3	0.765			
	RF4	0.727			

Table 5.7 continued

Infrastructure (INF)	INF1	0.882	0.933	0.947	0.75
	INF2	0.872			
	INF3	0.84			
	INF4	0.893			
	INF5	0.876			
	INF6	0.833			
Perceived pressure by journal (PPJ)	PPJ1	0.84	0.901	0.931	0.771
	PPJ2	0.88			
	PPJ3	0.908			
	PPJ4	0.881			
Organizational structure (OS)	OS1	0.86	0.875	0.914	0.726
	OS2	0.836			
	OS3	0.842			
	OS4	0.871			
Policy/guidelines (PG)	PG1	0.764	0.859	0.904	0.702
	PG2	0.883			
	PG3	0.865			
	PG4	0.834			
Social Attributes					
Community culture (CC)	CC1	0.916	0.926	0.947	0.818
	CC2	0.9			
	CC3	0.917			
	CC4	0.886			
Discipline norms (DN)	DN1	0.922	0.924	0.946	0.814
	DN2	0.92			
	DN3	0.911			
	DN4	0.855			
Dependent variable					
Data sharing practices (DSP)	DSP1	0.889	0.901	0.931	0.770
	DSP2	0.866			
	DSP3	0.872			
	DSP4	0.883			

iv. Discriminant Validity

This has been a process whereby a construct is essentially not similar from other constructs by experiential criterions. Consequently, discriminant validity suggests that a construct is distinctive and captures phenomena not described by other constructs in the model (Hair et al., 2014). Discriminant validity can be confirmed by calculating the squared AVE for each construct against correlations (shared variance) between the construct and all other constructs in the model. A construct must have satisfactory discriminant validity if the squared AVE exceeds the correlation among the constructs (Fornell and Larcker, 1981). In the following part, this study has tried to show the correlation of latent variables and discriminant validity based on Fornell-Larcker (table 5.11). Looking at Table 5.11 is it vividly showed that AVE for each construct is greater than each of the squared correlation between constructs. Consequently, discriminant validity is adequate for all of the constructs.

5.4 Assessing Structural Equation Assessment (Inner Model)

Once it is established that the construct assessments are truly reliable and valid, the following stage addresses the measurement of the structural model findings (Hair et al., 2014). This requires analyzing the predictive capabilities of the model and also the relationships between the construct. The main criteria for measuring the structural model in PLS-SEM is considered the measurement of collinearity among the predictor construct (VIF), the significance of the path coefficients, the level of the R^2 values and the predictive relevance (Q2), and the f^2 effect size. Below, each standard will be presented in detail.

5.4.1 Evaluating Significance and Relevance of the Structural Model

Bearing in mind the structural model, for each path linking latent variables represented a hypothesis. After the analysis conducted on the structural model, it permits the researcher to either confirm or disconfirm each hypothesis as well as understand the strength of the relationship between dependent and independent variables. Prior studies stated that the path coefficient value has to be at least 0.1 to account for a standard influence in the model (Joe Hair, Ringle, & Sarstedt, 2011).

By means of Smart-PLS algorithm output, the relationships between independent and dependent variables were tested. Conversely, in Smart-PLS in order to test the significant level, t-statistics for all paths are generated using the Smart-PLS bootstrapping function. Based on the t-statistics output, the significant level of each relationship is determined.

5.4.2 Coefficient Determination (R^2)

The R^2 is a measure of the model's predictive accuracy. One more way to eyesight R^2 is that it signifies the exogenous variable's combined effect on the endogenous variable(s). This effect ranges from 0 to 1 with 1 representing complete predictive accuracy. For coefficient of determination of this study, the R 2 value is high, at 0.722 can be seen in Appendix J and adjusted to 0.720 in appendix K. This number indicates that the exogenous constructs substantially explain the variation in the endogenous construct. According to Hair et al. 2017 as a rough rule of thumb, 0.25 is weak, 0.50 is moderate, and 0.75 is substantial.

Table 5.8: Results of the R^2 value

	R Square	R Square Adjusted
Organizational attributes	1.000	1.000
Social attributes	1.000	1.000
DSP	0.722	0.720
Personal attributes	1.000	1.000

5.4.3 Predictive relevance (Q^2)

Predictive relevance, Q^2, is acquired by the sample reuse technique called 'Blindfolding' in SmartPLS, where omission distance is set to 8 Hair et al., (2012) recommend a distance between 5 and 10, where the number of observations divided by the omission distance is not an integer). The blindfolding procedure with the cross-validated redundancy method (Stone-Geisser's Q^2 value) was applied for evaluating of predictive relevance of the proposed model. As there were 378 observations for this analysis. Due to thirteen endogenous constructs this method was assessed individually for model productivity.

The results of the construct cross-validated redundancy estimation are used to prove predictive relevance for a endogenous construct, the Q^2 value should be more than zero. For this study, Q^2 values emerges as 0.56. Since this number is larger than zero, is consider well above the threshold requirement which implies that the model has predictive relevance for these constructs.

Table 5.9: Results of coefficient of determination (R^2) and predictive relevance Q2

Endogenous Latent Variable	R^2 Value	Q2 Value
DSP	0.72	0.56

The blindfolding procedure with the cross-validated redundancy method (Stone-Geisser's *Q2* value) was applied for evaluating of predictive relevance of the proposed model. As there were 378 observations for this analysis. Due to thirteen endogenous constructs this method was assessed individually for model productivity. The results of the construct cross-validated redundancy estimation are used to prove predictive relevance for an endogenous construct, the Q^2 value should be more than zero. The model predictive relevance is measure by the Q^2 value of the endogenous variables. The Q^2 for data sharing practices is 0.56 Thus, the model is having a predictive relevance as the cutoff point is $Q^2 > 0$ (Cohen, 1988). This implies that the model has predictive relevance for these constructs.

Table 5.10: Correlation of Latent Variables and Discriminant Validity (Fornell- Larcker)

	ER	BNC	CFDS	DN	DR	DSP	RF	INF	PPJ	LC	CC	OS	EE	PG
ER	**0.811**													
BNC	0.313	**0.89**												
CFDS	-0.353	-0.201	**0.829**											
DN	0.248	0.39	-0.168	**0.902**										
DR	0.253	0.09	-0.139	0.047	**0.863**									
DSP	0.623	0.519	-0.361	0.525	0.332	**0.878**								
RF	0.229	0.3	-0.09	0.294	0.163	0.523	**0.765**							
INF	0.295	0.197	-0.103	0.259	0.264	0.424	0.222	**0.866**						
PPJ	0.315	0.316	-0.202	0.39	0.017	0.442	0.19	0.169	**0.878**					
LC	-0.334	-0.131	0.082	-0.185	-0.266	-0.454	-0.186	-0.326	-0.131	**0.896**				
CC	-0.312	-0.169	0.205	-0.162	-0.258	-0.428	-0.203	-0.235	-0.131	0.327	**0.905**			
OS	0.35	0.264	-0.207	0.278	0.136	0.444	0.222	0.113	0.301	-0.092	-0.193	**0.852**		
EE	-0.139	-0.126	0.057	-0.144	-0.144	-0.313	-0.073	-0.138	-0.105	0.31	0.111	-0.151	**0.774**	
PG	0.26	0.143	-0.086	0.145	0.118	0.317	0.148	0.211	0.164	-0.158	-0.245	0.21	-0.104	**0.838**

Table 5.11: The heterotrait-Monotrait Ratio of Correlations (HTMT)

	ER	BNC	CFDS	DN	DR	DSP	RF	INF	PPJ	LC	CC	OS	EE	PG
ER														
BNC	0.351													
CFDS	0.397	0.213												
DN	0.276	0.417	0.181											
DR	0.272	0.098	0.153	0.049										
DSP	0.699	0.56	0.393	0.574	0.347									
RF	0.291	0.34	0.124	0.341	0.192	0.625								
INF	0.316	0.206	0.107	0.276	0.278	0.459	0.269							
PPJ	0.359	0.338	0.222	0.422	0.03	0.484	0.222	0.181						
LC	0.367	0.141	0.088	0.2	0.272	0.498	0.228	0.352	0.141					
CC	0.341	0.178	0.22	0.175	0.27	0.467	0.243	0.249	0.145	0.352				
OS	0.403	0.288	0.23	0.309	0.154	0.5	0.269	0.127	0.339	0.102	0.212			
EE	0.15	0.115	0.085	0.138	0.175	0.337	0.156	0.161	0.109	0.37	0.128	0.159		
PG	0.293	0.155	0.093	0.162	0.122	0.354	0.19	0.23	0.177	0.17	0.272	0.242	0.124	

The amount of variance in the dependent variable is described by the independent latent variances by means of estimation of R^2 value. Generally, we have 3 types of R^2 value. R^2 value equal or above 0.75 is substantial. 0.50 is moderate and 0.25 is weak for the endogenous latent variable (Hair, 2014).

In this study, the R^2 value symbolize the extent of variance in the dependent variable explained by the independent variables. Table 5.13 displays the R^2 value obtained for this research. The model explains 77% of the variance for data sharing practice (DSP) which is considered substantial and good enough. Data sharing practice is predicted directly by all the constructs which are organizational structure (OS), infrastructure (INF), data repository (DR), research funders (RF), perceived pressure by journal (PPJ), policy/guidelines (P/G), discipline norms (DN), effort expectancy (EE), expected rewards (ER), community culture (CC), legitimate concerns (LC) and beneficence (BNC). Below table 5.13 shows the results of the R^2 and adjusted R^2. This implies that the model has predictive relevance for these constructs.

Table 5.12: Results of R^2 and Q2 Values in the model

Endogenous Latent Variable	**R Square**	**R Square Adjusted**	
Data sharing practices (DSP)	0.77	0.761	

5.4.4 Effect Size F ^{2}

The change in the R^2 value when a specified exogenous construct is omitted from the model can be used to evaluate whether the omitted construct has a basic impact on the endogenous constructs. This measure is referred to as the *f2* effect size. The effect size which will be found in appendix L can be calculated as

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}}$$

To assess the effect size of the predictor construct, Cohen's f^2 analysis (Cohen, 1988) is employed. This analysis follows the rule of thumb suggested by (Cohen, 1988) which considering the value of 0.35, 0.15 and 0.02 as large, medium and small effect size. The result indicates expected rewards (0.153) have a medium effect towards data sharing practices, Beneficence (0.08), have a small effect towards data sharing practices Conditions for data sharing (0.035), have a large effect towards data sharing practices. Discipline norms (0.088), Data repository (0.024), have a medium effect towards data sharing practices. Research funders (0.196), have a medium effect towards data sharing practices. Infrastructure (0.021), have a small effect towards data sharing practices Perceived pressure by journals (0.03), have a small effect towards data sharing practices, Legitimate concerns (0.052), have a small effect towards data sharing practices Community culture (0.031), have a small effect towards data sharing practices Organizational structure (0.03), have a small effect towards data sharing practices Effort expectancy (0.046), have a small effect towards data sharing practices and Policy/guideline (0.009) with also have a small effect towards data sharing practices. The guideline values for assessment of *q2* effect sizes are 0.02 (small), 0.15 (medium), and 0.35 (large) effects of predictive relevance of an exogenous variable (table 5.12).

Table 5.13: Result of effect size f^2 for all the exogenous variables for DSP

F^2	DSP
Expected rewards (ER)	0.153
Beneficence (BNC)	0.08
Community culture (CC)	0.035
Condition for data sharing (CFDS)	0.088
Data repository (DR)	0.024
Discipline norms (DN)	0.196
Research funders (RF)	0.021
Infrastructure (INF)	0.03

Table 5.13: Continued

Perceived pressure by journals (PPJ)	0.052
Legitimate concerns (LC)	0.031
Organizational structure (OS)	0.03
Effort expectancy (PE)	0.046
Policy/guidelines (PG)	0.009

5.4.5 VIF

Another assessment of collinearity is the variance inflation factor (VIF) which is described as the reciprocal of the tolerance (VIF= 1/TOL). Both the tolerance and VIF are considered in the regression analysis output of IBM SPSS. A variance inflation factor (VIF) states there is no correlation among the predictor variable examined and the rest of the predictors, therefore, the variance is not inflated. Nevertheless, whenever the VIF is greater than 5, the researcher ought to think of eliminating the corresponding indicator. In case of this study, the VIF is 3.998. Meanwhile this number is less than 5, thus, multicollinearity is not an issue. Once non-significant weights occur, scholars have to pay a serious attention to those assessments regarding collinearity diagnostic. Through PLS-SEM, there is a potential collinearity problem once a tolerance value is 0.20 or lower a VIF value is 5 (Hair et al., 2011). This study provides VIF analysis among every construct (independents variables) and data sharing practices (dependent variable). Based on the Table 5. the highest VIF between each construct and data sharing practices is belonging to "anticipated benefits" (VIF= 1.574) and the lowest is belonging to perceived effort (VIF= 1.139).

Table 5.14: Collinearity Assessment based on Variance Inflation Factor (VIF) for Data Sharing Practices VIF

Variables	VIF
Expected rewards (ER)	1.574
Beneficence (BNC)	1.337
Community culture (CC)	1.192
Condition for data sharing (CFDS)	1.411

Table 5.14: Continued

Data repository (DR)	1.2
Discipline norms (DN)	1.216
Research funders (RF)	1.281
Infrastructure (INF)	1.325
Perceived pressure by journal (JP)	1.397
Legitimate concerns (LC)	1.278
Organizational structure (OS)	1.29
Effort expectancy (EE)	1.139
Policy/guidelines (PG)	1.148

5.4.6 Bootstrapping Simulation

Bootstrapping is a technique which replaces theoretical assumptions and complex algebraic calculations with a large number of stochastic simulations. The heart of the idea is to use a computerized pseudo-random number generator in artificial resampling, and then to use these artificial samples to calculate an empirical probability distribution for the target statistics.

The results of boot strapping method (Table 5.15) demonstrate a p-value for each path and path coefficient will be found in appendix M. All structural model relationships were significant considering a p-value <0.05. In the model nine IV's had a significant positive coefficient which means, higher level of nine variables will tend to achieve a better data sharing practices and four IV's a negative significant coefficient which means, lowest level of four variables will tend to achieve an unhealthy data sharing practices. According to the results the effect of expected rewards (EE) on data sharing practices (DSPs) was positive and significant (β=0.235 , p<0.05) and it was more than the rest of the variables for example, beneficence which is positive and significant (=β 0.157 , P<0.05), conditions for data sharing is negative and significant (β = -0.098, P<0.05), discipline norms (DN) is positive and significant (β = 0.169 , P<0.05), data repository (DR) is positive and significant (β = 0.082, P<0.05), research funders (RF) also is positive and significant (β = 0.034, P<0.05), infrastructure is positive and significant (β = 0.039, P<0.05), perceived pressure by journals (PPJ) also is positive and significant (β =0.096, P<0.05) , legitimate concerns (LC) is negative and significant (β =-0.130, P<0.05), community culture (CC) also is negative and significant (β =-0.096, P<0.05), organizational structure has a positive and significant (β =0.094, P<0.05), Effort expectancy (EE) again is negative and significant (β =-0.110, P,0.05) and finally policy/guidelines (P/G) which is positive and significant (β = 0.049 , P<0.05).

Table 5.15: Path Coefficient (Inner Model) using Bootstrapping

Relationship	Original Sample (0)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Expected rewards – DSP	0.235	0.236	0.030	7.724	0.000
Beneficence -> DSP	0.157	0.156	0.030	5.293	0.000
Conditions for data sharing -> DSP	-0.098	-0.099	0.023	4.177	0.000
Discipline Norms -> DSP	0.169	0.168	0.028	5.963	0.000
Data repository -> DSP	0.082	0.083	0.027	3.061	0.001
Research funders -> DSP	0.234	0.235	0.026	8.970	0.000
Infrastructure -> DSP	0.079	0.079	0.023	3.365	0.000
Perceived pressure by journal -> DSP	0.096	0.096	0.029	3.283	0.001
Legitimate concerns -> DSP	-0.130	-0.131	0.027	4.788	0.000
Community culture -> DSP	-0.096	-0.096	0.025	3.889	0.000
Organizational structure -> DSP	0.094	0.093	0.030	3.111	0.001
Effort expectancy -> DSP	-0.110	-0.111	0.030	3.708	0.000
Policy/guidelines -> DSP	0.049	0.048	0.025	1.944	0.026

5.5 PLS Path Modelling Algorithm

PLS Path Modeling is a component-based estimation method. It is an iterative algorithm that separately solves out the blocks of the measurement model and then, in a second step, estimates the path coefficients in the structural model (Tenenhaus, 2008). It is a statistical method centered on linear regression? Correspondingly, the size and significance of path coefficients is also significant. The 95% bootstrap confidence intervals indicate that the path coefficient of 0.567 between the exogenous construct and the endogenous construct is significant; the path coefficient of 0.342 is also significant. The Path model of the research using the smart PLS is presented in figure 5.1.

5.6 Findings

1. **RQ4: What are the personal attributes that influence academics' data sharing practices?**

This analysis involves five (5) factors as personal attributes – the attributes are either positive or negative significant as can be seen below:

Table 5.16: Results of RQ 4 (Personal attributes)

	Original Sample (O) (Beta)	**P Values**	**Results**
Conditions for data sharing negatively influences data sharing practices	-0.098	0.000	Supported
Effort expectancy negatively influences data sharing practices	-0.110	0.000	Supported
Expected rewards positively influences data sharing practices	0.235	0.000	Supported
Legitimate concerns negatively influence data sharing practices	-0.130	0.000	Supported
Beneficence positively influences data sharing Practices	0.157	0.000	Supported

Based on the P Values, the finding from Table 5.16 suggests that personal attributes highly influence data sharing practices with 3 factors that is conditions for data sharing, perceived effort and legitimate concerns having negative influence against 2 factors (anticipated benefits and altruism) with positive influence. Having negative influence revealed that academics are conscious of sharing their data with others which may be as a result of mistrust or the energy needed in sharing. While for those with positive influence are because of the reward expectations attached to the sharing practices.

ii. RQ5: What are the organizational attributes that influence academics' data sharing practices?

This analysis involves six (6) factors as organizational attributes – all attributes are positive significant as can be seen below:

Table 5.17: Results of RQ5 (Organizational attributes)

	Original Sample (O) (Beta)	P Values	Results
Organizational structure positively influences data sharing practices	0.094	0.001	Supported
Infrastructure positively influences data sharing practices	0.079	0.000	Supported
Data repository positively influences data sharing practices	0.082	0.001	Supported
Research funders positively influences data sharing practices	0.234	0.000	Supported
Perceived pressure by journals positively influences data sharing practices	0.096	0.001	Supported
Policy/guidelines positively influences data sharing practices	0.049	0.026	Supported

Table 5.17 suggests that all six organizational attributes have positively influence data sharing practices. Considering these factors, academics believed hierarchy of their organizations supported data sharing by providing relevant policies/ guidelines or conducive environment for such practices.

Looking at Table 5.18, it is also agreed that having infrastructure and data repositories promote data sharing among academics. Activities of funding agencies and journal publishers are not left behind in persuading academics' data sharing. All these factors their P value are less 0.005 thus, are all significant.

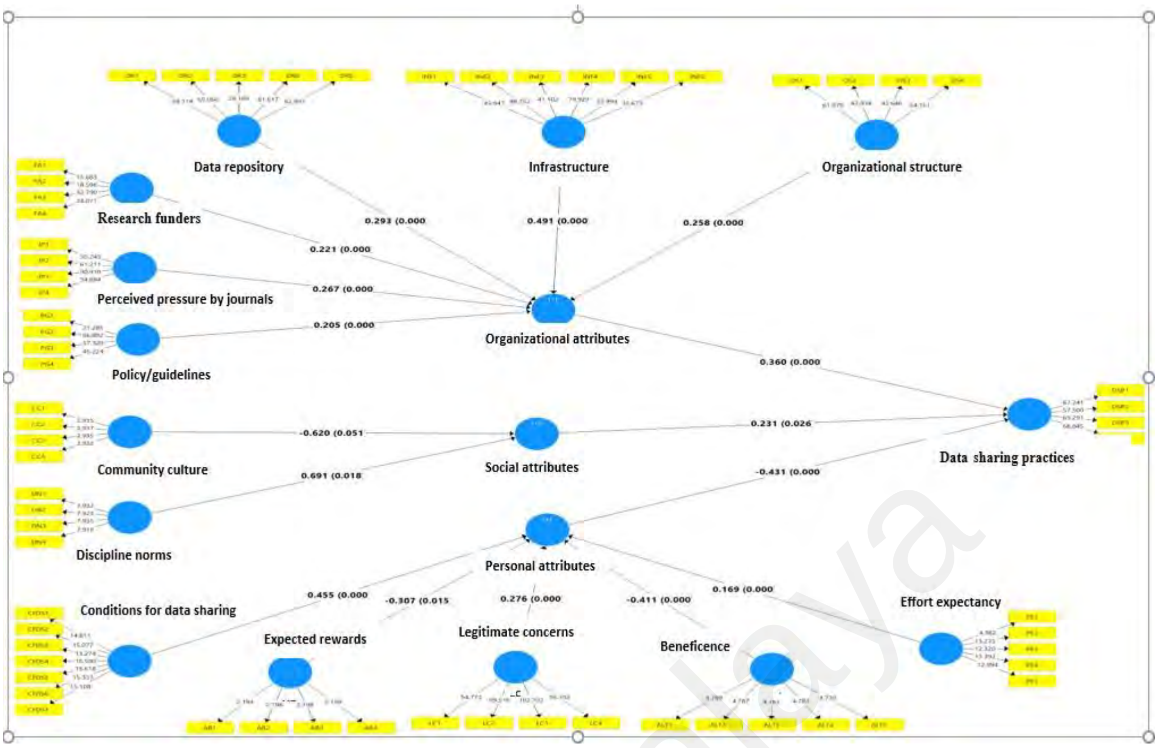

Figure 5.1: Path Model of the Research

ii. RQ6: What are the social attributes that influence academics' data sharing practices?

This analysis involves two (2) factors as social attributes (community culture and discipline norms) – all attributes are either positive or negative significant as can be seen below:

Table 5.18: Results of RQ 6 (Social attributes)

	Original Sample (O) (Beta)	P Values	Results
Community culture negatively influences data sharing practices	-0.096	0.000	Supported
Discipline norms positively influences data sharing practices	0.169	0.000	Supported

Bearing in mind the P Values, table 5.18 findings suggest that factors under social attributes also influence data sharing practices with community culture having negative influence and discipline norms with positive influence on data sharing among the academics. The negative influence of community culture was as a result of how people in the communities under study believed in monopolizing what they owned. While for discipline norms, scholars in their various disciplines do encourage sharing.

iv. RQ7: What are the differences in research data sharing practices between social sciences and sciences?

This section makes a contribution to the debate regarding the differences in research data sharing practices among social sciences and the sciences. To effectively find this difference, the researchers distributed the questionnaire based on the various faculties among the five universities.

Table 5.19: Respondents among the five Universities under study

University	No of returned questionnaires	DSP among faculty of social sciences	DSP among faculty of Sciences	DSP among other faculties
ATBU	100	39 (39%)	36 (36%)	25 (25%)
MAUTECH	105	40 (38%)	38 (36%)	27 (26%)
FUK	57	23 (40%)	19 (33%)	15 (27%)
FUW	63	28 (44%)	20 (32%)	15 (24%)
FUY	53	22 (42%)	20 (37%)	11 (21%)
TOTAL	378	152	133	93

From table 5. 19, showed that data sharing practices occur mostly among sciences than social sciences disciplines. That sciences slightly share data with (SD=.89835) more than the social sciences with (SD=.88358).

The researcher intent to investigate the differences that exist between the two main faculties that is faculty of science (3) and faculty of social sciences (4). Firstly, the researcher calculates the number of respondents among each faculty in the universities under studies. Therefore, the following calculation were conducted;

An independent-samples t-test was conducted to compare difference between sciences and social science disciplines.

There was not a significant difference in the scores for Sciences (M=2.9746, SD=.89835) and Social Sciences (M=2.9877, SD=.88358)

Therefore, there was not a significant difference in the scores for sciences (M=2.9746, SD=.89835) and social sciences (M=2.9877, SD=.88358).

Table 5.20: Group Statistics

	Faculty	N	Mean	Std. Deviation	Std. Error Mean
DSP.M	3	133	2.9746	.89835	.08270
	4	152	2.9877	.88358	.06921

i. These results suggest that sciences have little differences with social sciences regarding research data sharing.

Considering the findings obtained from table 5.20 calculations, it is evidently showed that scientists sharing research data slightly more than social scientists. Looking at both the means and the standards deviation of the sciences are higher than the social sciences. This has been proving by calculating the means and the standard deviation.

Table 5.21: Differences in Data Sharing Practices of each Construct between Faculty of Sciences and Social Sciences.

	Faculty	N	Mean	Std. Deviation
Discipline norms (DN)	Sciences	133	3.5869	1.27240
	Social Sciences	152	3.6304	1.24640
Expected rewards (ER)	Sciences	133	3.3136	.75616
	Social Sciences	152	3.3896	.69339
Perceived pressure by journal (JP)	Sciences	133	3.8877	.89431
	Social Sciences	152	3.7899	1.01946
Data repository (DR)	Sciences	133	2.2356	.92436
	Social Sciences	152	2.3558	1.02560
Effort expectancy (EE)	Sciences	133	3.3627	.81898
	Social Sciences	152	3.4577	.82034
Legitimate concerns (LC)	Sciences	133	3.8602	1.04827

	Social Sciences	152	3.9540	.90704
Beneficence (BNC)	Sciences	133	3.7237	1.09323
	Social Sciences	152	3.7546	1.02856
Conditions for data sharing (CFDS)	Sciences	133	3.8535	.82952
	Social Sciences	152	3.6757	.95331
Organizational structure (OS)	Sciences	133	3.7119	.76908
	Social Sciences	152	3.7776	.81508
Community culture (CC)	Sciences	133	3.6886	1.18120
	Social Sciences	152	3.8037	1.11345
Infrastructure (INF)	Sciences	133	2.3037	1.06655
	Social Sciences	152	2.2669	.95124
Policy/guidelines (PG)	Sciences	133	2.9322	.72402
	Social Sciences	152	2.9893	.62010
Expected rewards (ER)	Sciences	133	3.0466	.86599
	Social Sciences	152	3.0567	.91721
Data sharing practices (DSP)	Sciences	133	2.9746	.89835
	Social Sciences	152	2.9877	.88358

From table 5.21, it is showed that sciences share data more than the social sciences even though there was not a significant difference. Correspondently, many scholars have argued that the social sciences are unlike the natural science because they involve a kind of interpretive inquiry which has no parallel in the natural sciences, so, also their research data.

The literature consulted and the survey instrument used for this research have gaudily revealed this assertion. Studies revealed wide disparities in the philosophy and practices of data sharing among disciplines which showed every respective academic field has different approaches use and charge in their data-sharing practices (Kim and Stanton, 2013).

Social science data encompass interpretations regarding human subjects and unstructured formats for instance, interview, transcript, observation notes, and survey data (Yoon and Kim, 2017). To scientists, their data mostly comes through scrutinizing the original data, they, repudiate research findings, which aids avert scientific blunders or misconducts such as deception or pick out reporting.

5. 9 Summary

In this chapter, the results survey findings, the confirmatory phase have presentedand discussed. The data collection procedure resulted to a sample total of 378 valid participants in 5 Nigerian universities that include Abubakar Tafawa Balewa University (ATBU), Modibbo Adama University of technology Yola (MAUTECH), Federal University Kashere (FUK), Federal University Taraba (FUT) and Federal University Yobe (FUY) for the data analysis. These survey participants are only the academic staff of the above-mentioned institutions. Immediately the survey data were put together, data cleaning was piloted in terms of accuracy of the data collected, outliers, and response-set. Structural equation modeling (Partial Least Squares; PLS) was applied to test the research hypothesis and evaluate the research hypothesizes. The results were analyzed based on the reliability and validity through convergent validity, discriminants validity, cross loading, variance inflation factor (VIF), common-method variance (CMV), normality test and outlier test. The result further indicates that there are both positive and negative significant relationship among the independent variables (IV) and the dependent variable (DV).

The path coefficient indicated as follows; for personal attributes they are expected rewards (0.235), altruism (0.157), conditions for data sharing (-0.098), perceived effort-0.110 and legitimate concerns (-0.130). Organizational attributes are data repository (0.082), research funders (0.234), infrastructure (0.079), journal publishers (0.096), organizational structure (0.094) and policy/ guidelines (0.049). Social attributes have discipline norms (0.169) and community culture (-0.096),

This showed about four constructs (Condition for data sharing, Legitimate concerns, Organizational culture and Perceived effort) are having negative significant relationship with data sharing practices. The result for convergent validity shows all the variances are significant with P value of less than 0.005 as indicated in the table 5.16 in chapter five above.

The result for discriminant validity also indicated that all the items are above 0.7 as indicated by Fornell- Larcker in table 5.11. The inner VIF values indicated as follows; Expected rewards (1.574), Beneficence (1.337), Conditions for data sharing (1.192), Discipline norms (1.411), Data repository (1.2), Research funders (1.216), Infrastructure (1.281), Perceived pressure by journal (1.325), Legitimate concerns (1.397), Community culture (1.278), Organizational structure (1.29), Effort expectancy (1.139) and Policy/Guidelines (1.148).

The outlier showed the minimum of -3.350 and the maximum is 3.069 and the normality test results fall in between -.1341 to 1.245 these are clearly indicated in table 4.4 and 4.5 respectively.

The outcomes of the demographic information specified that out of the total 378 participants 301 were male (79.6%) and 77 (20.4%) were female. For their age bracket, those with the highest were those between 31-35 years with 169 (44.7%) and the least fall between 21-25 years 17 (4.5%). Regarding the experience of the survey participants, the results indicated that those between 11-15 years' experiences were the highest with 138 (36.5%) and the lowest were those with < 5 years 22 (5.8%). Concerning the faculties, social sciences were the larger with 163 (43.1%) while the least were those from the other faculties 14 (3.7%). Finally, the results for the qualification showed those with master's in science (M.Sc.) were the largest with 220 (58.2%) followed by PhD 73 (19.3) and the least were B.Sc. with 8 (2.1%). According to the research model, in the first model the effect of thirteen independent variables including expected rewards, beneficence, conditions for data sharing, discipline norms, data repository, research funders, infrastructure, perceived pressure by journals, legitimate concern, community culture, organizational structure, effort expectancy, and policy/guidelines were evaluated on data sharing practices. According to the results the effect of all the constructs on data sharing practices (DSPs) were significant with nine having positive significant and four with negative significant. Since the data sharing practices defined as the dependent variables, this study provides VIF analysis between each of the 13 constructs (independents variables) and data sharing practices (dependent variable). Considering the conclusions of the results, the highest VIF between each construct and data sharing practices is belonging to "expected rewards" (VIF= 1.574) and the lowest is belonging to effort expectancy (VIF= 1.139).

CHAPTER 6: DISCUSSION AND CONCLUSION

6.1 Introduction

The current research aimed to explore data sharing among academics among in Nigeria. This chapter encompasses the summary of this research findings as well as offers conversation of the discoveries that emerged from this research and the consequences of the study at different level research. An interview with some of the academics was conducted and the findings were utilized in developing of the survey instrument by offering additional variables. Based on the findings acquired in this research, each result was separately evaluated and measured together using previous studies.

The present chapter was divided into five sections. The first section began with the introduction, then the concluding remarks which summarized the findings of the current research based on research objectives. Then explained the constructs using theory of organizational culture and followed by enlightening the challenges faced by the researcher during the data collection. The fifth and the final section will present the contributions, limitations and future research and recommendations and then the conclusion.

6.2 Concluding Remarks

Data sharing in university have been strongly advocated in recent time, there are diverse perceptions from the scholars regarding this concept. This study is to scrutinize data sharing perceptions and practices among academics. This summary of these findings can be done based on the two research objectives intended of the current study.

Research objectives 1, to examine the perceptions of research data sharing among academics.

To achieve this objective, interviews were conducted and the findings for these interviews revealed the awareness, understanding and familiarity of data sharing practices by the academics. This has further revealed funding agencies, discipline receptiveness and journal publisher as themes under awareness of data sharing. Helping others, collaborations, cost and time as some of the themes for understanding. While familiarity of academics towards data sharing is through platforms such as figshare, Gift-cloud, personal website and data repository.

In furtherance, the interviews also show the motivations of data sharing to academics. The respondents have mentioned many things that motivated them to participate in research data sharing. These motivations are both intrinsic and extrinsic in nature. Respondents cited things such as looking for more citations, exchange, reputation, academics promotion, monetary incentives, protecting data against misconduct among others.

Other revelation from the interviews are the perceived risks for academics in sharing their research. The responses from the respondent were grouped into two basic themes that is respondents mentioned data privacy and cultural orientations as related risks associated to data sharing among academics in Nigeria. Under data privacy as theme, there were confidentiality, misused and mistrust as some of the subthemes. While for cultural orientation culture and community belief turn out to be the subthemes.

In a nutshell, findings of the research objective 1 which investigate the perception of academic regarding data sharing revealed different perceptions by academic regarding the concept "research data sharing". Some academics considered the term data sharing as a chance to help other scholars in their effort to build their own research. Other look at it as openness and transparency of research materials, a critical issue in academic which if properly observed can contribute to the advancement of academic research". But then some few once perceived it as is a process of making investigators lazy and an act of plagiarism. Thus, it is vividly clear that different academics have perceived research data sharing differently. While some are against the practice, majority of the academics considered as a welcome development in the academic environment. The finding further revealed different motivations such as more citations, academic promotion recognition, monetary incentives and protecting data against misconduct among others. The result also shown some perceived risks related to data sharing among academics for example, concern about data privacy and cultural orientations are some of the identified risks. The findings from these interviews however, aid in providing relevant variables for the development of the survey instrument, which was used to address research question 4, 5 and 6.

Research objectives 2; to investigate the factors that influence academics' data sharing practices. In achieving this objective, survey instrument (questionnaire) were distributed to the participants. The findings for this research objectives revealed that 13 variables were found to be those attributes that influence academics' data sharing. This following section summarized the findings based on the theory of organizational culture. They are as follows:

(i) Artifacts refers to those "characteristics of the organization which can be easily viewed, heard and felt by individuals" (Dhir 2019). The following are constructs based on artifacts namely:

Infrastructure

Infrastructure was found to have positively determined academics' data sharing practices. This means that academics considered having infrastructure can enhance participation in research data sharing practices. This outcome backings previous studies' verdicts that infrastructure such as training (Van den Eynden & Corti, 2017), platforms (Cao, Giyyarpuram, Farahbakhsh, & Crespi, 2017), and connectivity (Roberts, Anderson, Skerratt, & Farrington, 2017) all influence academics' data sharing practices. Sharing data requires both technical and research skills that are obtainable via training. Platform is generally wish to offer a reliable data sharing through development of data usage comprehensibility and traceability and to ease data sharing practices in academics, the provision of functional linking devices for potential sharing and reuse of the dataset is inevitable.

Organizational Structure

In this research, organizational structure was also acknowledged to have a significant positive in determining academics’ data sharing practices. By implications, organizational structure in university determines and regulates data sharing practices, because the top management decision at times determines the activities of the universities including data sharing practices. Any administration that is in love with sharing can surely encourage data sharing. This has been cited severally in some of the previous research. For instance, “An administrator that help in coordinating different units to share knowledge is considered it critical in enhancing an organization's capabilities and would always support it” (Kogut & Zander, 1992). The impact of organizational structure on research data sharing depends on the kind of structural mechanisms used by such an organization towards sharing or withholding their research data.

Data Repository

Data repository was realized to have a significant positive effect on academics’ data sharing practices. This shows that the availability of data repositories in universities had increased academics’ data sharing practices across different disciplines. It motivates other investigators to share their data with their colleagues in respective of their disciplines.

For this reason, academics discussed the prominence of data repositories as its relates to data sharing (Cragin, Palmer, Carlson, & Witt, 2010; Marcial & Hemminger, 2010). It is therefore a reality that data repositories aid became relevant for data sharing in facilitating research (Marcial and Hemminger, 2010). While the absent of data repositories can depress academics towards sharing their data (Cragin et al., 2010). Therefore, academic environments need to change and improve their data repositories by means of providing relevant data and establishing privacy policy to protect data sharing using data repositories.

Research funders

This was similarly known to have a significant relationship with academics' data sharing practices, and this finding is corresponded with some preceding studies piloted. Earlier researchers established that policies created by research funders similarly attained positive impacts on academics' data sharing (McGuire, Hamilton, Lunstroth, McCullough, & Goldman, 2008). Therefore, this research revealed a substantial connection concerning funding agencies and academics' data sharing practices. Furthermore, it is possible that majority of the academics considered funding agencies' policies concerning data sharing as a thoughtful pressure.

Several participants observed that national research funders sometimes do make compulsory data sharing policies and researchers identify certain forcible pressures from funding agencies. One of these academics a professor in engineering declared: "There are certain funding pressure on researchers to participate in data sharing, some of these funding agencies require sharing of research data". This demonstrates that certain policies were made mandatory by funding agencies (NSF and NIH), researchers see it as a coercive pressure thus, determines how they can involve in its practices.

Perceived Pressure by Journals

The current study admitted that journals' publishers has a weighty control on academics' data sharing practices. This outcome proves that journals exercise certain intimidating burdens on academics' data sharing practices. thus, the results are consistent with other preceding bibliometric studies' conclusions which stated clearly the positive correlations concerning the presence of data sharing policy in journals and the rate at which researchers place data in public databases (Piwowar and Chapman, 2010). Conversely, further studies claimed there was not significant effects of data sharing policies created by journals on academics' sharing practices rates (Cech et al., 2003).

Related to previous studies, the current study looks at the relationship between journals publishers and academics' data sharing practices across diverse disciplines, only to realize that pressure by journals positively rises academics' data sharing practices. Majority of journals in some disciplines particularly in biological sciences have demanded researchers to deliver data either by way of additions or in data repositories that serves as a condition for publication, and at the same time, a lot of journals have applied data sharing policies which necessitate authors to share data via placing into data repositories (Weber, Piwowar, & Vision, 2010). This research demonstrates actuality of a noteworthy connection concerning the burden by journals publishers and academics' data sharing practices.

Policy/Guidelines

This research found that policy/guidelines operate in universities significantly determine academics' data sharing practices across different disciplines. Previous studies had never scrutinized the relationship between the policy/guideline in the universities and the academics' data sharing practices yet. The present investigation revealed the substantial connection between established policy/guideline and positively determines academics' data sharing practices. This finding supports the idea of prior studies that have measured institutional policies on digital research data practices (Wouters, 2002).

This current research further indicates policy/guidelines vary through diverse disciplines in universities, and these policies/ guidelines play an important role in participation of academics' sharing practices. Consequently, researchers in those field of studies with sound policy/guidelines towards data sharing practices are expected to make their data accessible to other investigators. Consequently, in the disciplines with less or no relevant policy/guidelines towards data sharing practices are not expected to make data reachable to the public.

(ii) Espoused Beliefs and Values refers to the “organization’s stated values and rules of behaviour” (Ramgutty-Wong & Dusoye, 2011). It is how the members represent the organization both in terms of their behavior and the shared values. The following are constructs based on espoused beliefs and values namely:

Conditions for Data Sharing

Conditions for data sharing was found to have a negative significant, even though scholars are always prepared to freely make their data available to others (Wallis et al., 2013). Researchers like to put certain conditions that would guarantee the safety and privacy of their data, this is in conformity with other prior studies, Researchers feel there are certain situations that may warrant them to share data without tricky hence placed some conditions among which are: privileges to publish results, appropriate acknowledgement to the data source, acquaintance both the data donor and the beneficiary, funding agency anticipations, and the total effort required to share among others (Wallis et al., 2013).

Prior studies argued that lack of trust necessitates researchers to place conditions before sharing data. For some researchers, both the data sharer and recipient must develop certain level of trust among them before sharing can take place. A trust can encourage researchers to exchange knowledge and improve value through that particular exchange (Holste and Fields, 2010). It is vital for researchers when thinking about data sharing (Knoppers et al., 2011).

Effort Expectancy

This is in the same way recognized to have a significant negative effect on academics’ data sharing practices. By implication, academics who notice that involving in data sharing requires more effort may probable not willing to share their data with others.

During the interview, academics emphasized that the sweats needed in accomplishing data sharing avert most of them to participate in sharing their data with other researchers even within the same discipline. This result backs some past studies' arguments that the sweats and labor such as requiring extra exertion, charge, and or time in data sharing deject academics in their effort to share their data. This result is likewise applicable to what Tenopir and colleagues 2011 freshly discovered: academics hardly reveal their data online for the reason that there are less time and finance to arrange their data.

Data sharing normally needs much more time, cost and energy for academics to create and make data freely accessible. Researchers must sacrifice time by organizing and arranging data to other investigators, and on occasion these data donors must as well sacrifice certain period to offer extensive clarifications regarding their data for easier comprehending by their beneficiaries. Therefore, numerous researchers have worries on the kind of efforts required in data sharing, for this reason, perceived effort negatively determines academics' data sharing practices. One of the researchers in education stressed the concern of additional strength anticipated in data sharing, saying: "Effort needed in explaining data to another scholar is even more disheartening than the work required in generating the data".

Expected rewards

This was likewise accepted to obtain a significant positive inspiration on academics' data sharing practices. Therefore, those academics that notice the anticipated benefits in the course of involving in sharing practices are more likely to make data readily available to many. This outcome supports previous research's findings such as professional recognition by (Kim, 2017), institutional recognition (Kankanhalli, Tan, and Wei,2005). and academic rewards (Nosek et al., 2015) all encourage academics' data sharing practices. Recognition and improving status through increased citations, acknowledgement and conceivable praises are related with the concept of perceived benefits.

Prior studies in some areas like knowledge sharing similarly revealed that anticipated rewards from knowledge sharing behavior have a positive effect on individuals' attitudes concerning knowledge sharing and their intentions to share knowledge (Park & Gabbard, 2018). Findings from this study indicates that researchers ascertain further benefits via recognition and reputation are for sure more eager to share data compare to those that do not. This verdict is also allied to Hull, Farmer, and Perelman (2018). whom finding stated that articles that delivered appropriate data sets by means of data repositories expected extra citations as compare to those articles without data sets.

Beneficence

It is similarly discovered this was recognized to have a positive significant relationship with data sharing practices. This discovery come to an agreement with series of earlier studies' findings which stated altruism to be an important factor which substantial influence on data sharing practices having revealed that (Zenk-Möltgen, Akdeniz, Katsanidou, Naßhoven, and Balaban, 2018), in the perspective of knowledge sharing, altruism was comprehensively investigated and realized to possess noteworthy control on knowledge sharing (Reichert & Sohn, 2019).

Different prior researches in information sharing explained the word altruism to be a type of intrinsic motivation which involve acquiring psychological benefits like contentment and delight in assisting others (Platt, Jacobson, & Kardia, 2018; Sun, Jiang, Hwang, & Shin, 2018). However, this research considers "altruism" by labelling it as the willingness of a person to work towards increasing others' well-being and contribute to societies without anticipating something in return (Hsu & Lin, 2008). This study further indicates that altruism inspires researchers to help other researchers to save time and effort, permitting them to discover something lost in the original research and backing to research development in academic field of studies via data sharing.

Legitimate Concerns

In this research, legitimate concerns were correspondingly established to have a negative significant relationship with data sharing practices. This has to do with the potential uncertain and negative outcomes in the process of sharing data. Prior researches argued that researchers consider data sharing to be a great loss in various areas for instance, losing publication opportunities, misuse and misinterpretation of data by the potential users. This made academics unwilling to share data (Denzin & Giardina, 2018). Nevertheless, this research found significant negative relationship between legitimate concerns and researchers' data sharing practices.

One of the conceivable reasons for this negative significant result in this research is that data sharing become risky and put doubt in whether to make their data available or not with other researchers. Therefore, affects researchers' career undesirably. In social science for example, researchers become worrying when they view sharing data may lead to misuse and criticism by peers. These risks potentially may have negative impact on researchers' career (Kim, Lee, and Elias, 2015). Also, privacy serves as a legitimate concern as several investigators have indicated that privacy is another important factor that influences how researchers go about sharing their data. The frequent finding of flaws in data anonymization and of course the issue of data mining resulted to ethical and privacy concerns in data sharing (Takashima et al., 2018). It is observed that researchers show worries in participating in data sharing practices especially those that involved data of unpublished work.

Another finding of this study is the different in data sharing between sciences and social sciences. This paragraph makes a contribution to the debate regarding the differences in research data sharing practices among social sciences and the sciences scholars. Many scholars have argued that the social sciences are unlike the natural science because they involve a kind of interpretive inquiry which has no parallel in the natural sciences, so also their research data. The literature consulted and the survey instrument used for this research have gaudily revealed this assertion. Studies revealed disparities in the philosophy and practices of data sharing among disciplines which showed every respective academic field has different approaches use and charge in their data-sharing practices (Kim and Stanton, 2013).

Social science data include explanations on human subjects and unstructured formats for instance, interview, transcript, observation notes, and survey data (Yoon and Kim, 2017). To scientists, their data mostly comes through scrutinizing the original data, they, repudiate research findings, which aids avert scientific blunders or misconducts such as deception or pick out reporting.

(iii) Basic Underlying Assumptions

Basic assumptions as one of the third level of organizational culture "are deeply embedded, taken-for-granted behaviors which are usually unconscious, but constitute the deep essence of culture. These assumptions are well integrated in the work culture, that they are easily recognized in actions of the employees and management" (Duerr, Holotiuk, Wagner, Beimborn, & Weitzel, 2018).

Community Culture

The culture of the universities' community was established to have a negative significant correlation with academics' data sharing practices. The outcome is quite different when compare to what previous research maintained, past studies established community culture to have positive significant that community culture may also be thought of as knowledge resource because it provides the context within which community members generate, attain, share, and manage knowledge (Holsapple & Joshi, 2004). Though, our study has found a negative significant correlation between community culture and academics' data sharing practices. The disagreement of the discoveries between past studies and the current research may be as a result of the differences in cultures operate among the communities that these studies were conducted. As prior studies must have focused on Europe and American organizational culture while this was conducted on Africa.

Many scholars argued that in every community, culture is expected to adjust employees' attitudes and activities towards promoting sharing of data or knowledge between them. "In most of the communities, there is need for major cultural shift to amend employees' attitudes and activities in order to readily and constantly share their knowledge" (Alavi & Leidner, 2001). Thus, a community's culture is the collective principles, thoughts, and standards that have emotional impact on community's performance (Jones, Cline, & Ryan, 2006). Therefore, it can be concluded that organizational culture has negative significant influence on academics' data sharing practices among academics in Nigerian universities.

Discipline Norms

This research proven that discipline norms has a momentous impact on academics' data sharing practices. This discovery confirms that discipline norms positively determine academics' data sharing practices. In other word, those discipline with norms that encourage sharing are likely to partake in data sharing as compare with those without such norms. This result is in line with some of the preceding research's conclusions that there are positive correlations between the presence of discipline norms and the rate at which academics share their research data. Some disciplines as norms, they considered data sharing as part of their professional responsibility and are expected to value and involve deeply in data sharing practices most as they feel pressure from their colleagues to share data (Kim and Stanton, 2012). Other researchers have the belief that those constantly shared data usually improve their research performance (Kim and Stanton, 2012). Current research expresses that academic perceive more data sharing when a discipline as a norm are ready to support data sharing, this increases their willingness to sharing.

6.3 Challenges during Data Collection

In this section, the researcher highlights the challenges and difficulties and explains how he overcomes those challenges. One of the most challenging aspect of this study is the financial capability of the researcher, the researcher has frequently faced with the problem of money in case of transportation, feeding and accommodation in the process of undertaken this study.

Another challenge is related to the limited cooperation and reluctant of some of the participants to be interviewed. The process to convince the academics to participate in this study was not an easy task. It was very important to achieve a satisfactory response rate for this study as possible. The researcher has to visit each participant individually in their offices and talk to them gently and state the significance of this study and how this study will benefit the participants themselves in improving the research in their faculties and to the university community. This dilemma was not easy to overcome. To overcome the challenge, the researcher asked his relatives who knew few professors at some of these universities under study to help him in asking them to participate in the interview and in the questionnaire.

Again, there was problem of time and effort in the process of making an appointment with the participants for interview. The researcher has to call majority of the participants by telephone to arrange the date to conduct the interview. Unfortunately, the interview appointments often needed to be rescheduled because the some of the participants are always busy. This increases the workload and also time consuming. In addition, rigorous weather condition (winter season) during the process of data collection made the interview appointments and distribution of the questionnaire on hold and delayed the process of data collection.

6.4 Research Contributions

Even though this research has some number of limitations, it has helped to clarify the ways in which academics share data most importantly has captured the perceptions and factors influence data sharing. The contributions of this research has been categorized in to three (3) that include contribution to the body of knowledge, theoretical and practices contributions.

Body of knowledge

This study addressed issues related to awareness, understanding, familiarity, motivations and risks involved in data sharing among academics in Nigeria. Despite the significant of data sharing by academics (Borgman, 2015). in Nigeria, there are limited previous studies investigating this area. This study addresses this issue by investigating data sharing practices of academics in Nigeria. In other word, this study filled the knowledge gap about research data sharing and promoting data sharing culture by exploring how academics perceived the concept of data sharing and the factors that influence such practices.

Theoretical

This section on theoretical contributions addresses how the research findings of this study contribute pleasantly using the theory employed in this research. Current study developed a framework by categorizing all the research variables to suit the three (3) layers in the theory of organizational culture by Schein, 1990. The framework shows data sharing practices of academics are influenced by organizational attributes (organizational structure, infrastructure, data repository, funding agencies, journal publishers and policy/guidelines), personal attributes (conditions for data sharing, perceived effort, anticipated benefits, legitimate concerns and altruism) and social attributes (community culture and discipline norms) have significant influences on academics' data sharing behaviors. This research also assists in discovering new items such as community culture and infrastructure.

Practices

This study data sharing practices of academics are driven by motivation intrinsic (more citations, academic promotions and reputations) and extrinsic (monetary incentives, exchanges and protecting data against misconduct). These motivations would encourage the participation of academic towards data sharing practices in Nigeria. Practically, findings presented here can help the academics, journal publishers and public agencies to know the perceived risks in data sharing, promoting the sharing and reuse of research data and understanding the sources where academics became aware of data sharing. This study has further takes in to account the distinct of data sharing practices between social sciences and science scholars.

6.5 Limitations of the Study

Having made much effort to find solution to any established limitations that may be found in this research, this research however, has some distinguished limitations in the following areas that are pointed as; (1) generalized survey instrument, (2) constraints of sampling strategy, (3), small group size for the faculties during the interview.

In spite of the above-mentioned limitations, this study permits to inspect in what way theory of organizational culture suits a research on research data sharing practices through different disciplines. This could be the earliest empirical research using theory organizational culture that is related to research data sharing practices. Upcoming investigation should be able to expand the current study through seeing the aforesaid limitations, and the researcher offered promising guidelines for such upcoming study concerning research data sharing practices.

6.6 Future Research and Recommendations

Currently, this part offers recommendations designed for upcoming study regarding the results found from this research. Forthcoming research can;

(1) Extending the study to other research organizations. First and foremost, forthcoming study in research data sharing practices ought to extend the study beyond universities. Research on this topic should as a matter of fact be conducted in related research organization to compare the findings.

(2) Coming study should review some of the discovered research constructs. By conducting study on similar topic would give opportunity in reviewing some of these identified constructs to see the actual relationship with the dependent variable.

(3) Future study should scrutinize factors influence research data sharing practices. It is also advisable to coming research should examine carefully the factors that influence data sharing practices and to see whether there will be a different with the ones obtained in this study.

(4) Finally, upcoming study requires to scrutinize how researchers detect, interpret and comprehend, existing data sets for their own research in view of a data reuse perspective.

References

Abbott, D. (2015). Digital curation and doctoral research. *International Journal of Digital Curation, 10*(1), 1-17.

Abowd, J. M., Schmutte, I. M., & Vilhuber, L. (2018). Disclosure Limitation and Confidentiality Protection in Linked Data.

Abubakar, M., Musa, A., Ahmed, A., & Hussaini, I. (2007). The perception and practice of traditional medicine in the treatment of cancers and inflammations by the Hausa and Fulani tribes of Northern Nigeria. *Journal of Ethnopharmacology, 111*(3), 625-629.

Achenbach, J. (2015). The new scientific revolution: Reproducibility at last. *The Washington Post*.

Adam, I., & Usman, I. (2013). Resource sharing services in academic library services in Bauchi: the case of Abubakar Tafawa Balewa University and Muhammadu Wabi Libraries, Federal Polythecnic, Bauchi. *Merit Research Journal of Education and Review, 1*(5), 001-005.

Adeniji, A., Salau, O., Awe, K., & Oludayo, O. (2018). Survey datasets on organisational climate and job satisfaction among academic staff in some selected private universities in Southwest Nigeria. *Data in brief, 19*, 1688-1693.

Agosti, M., Ferro, N., & Silvello, G. (2018). Digital libraries: from digital resources to challenges in scientific data sharing and re-use. In *A Comprehensive Guide Through the Italian Database Research Over the Last 25 Years* (pp. 27-41): Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211.

Akers, K. G., & Doty, J. (2013). Disciplinary differences in faculty research data management practices and perspectives. *International Journal of Digital Curation, 8*(2), 5-26.

Akintola, S. O. (2018). Legal implications of data sharing in biobanking research in low-income settings: The Nigerian experience. *South African Journal of Bioethics and Law, 11*(1), 15-19.

Akintoye, E. O., & Uhunmwuangho, S. O. (2018). Analysis of the effects of frequent strikes on academic performance of students in universities in Nigeria: Edo State as a focal point. *African Research Review, 12*(1), 56-65.

Alam, A., Malik, I. A., Abdullah, A. B., Hassan, A., Awan, U., Ali, G., . . . Naseem, I. (2015). Does financial development contribute to SAARC′ S energy demand? From energy crisis to energy reforms. *Renewable and Sustainable Energy Reviews, 41*, 818-829.

Alavi, M., & Leidner, D. E. (2001). Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS quarterly*, 107-136.

Ali, F., Rasoolimanesh, S. M., Sarstedt, M., Ringle, C. M., & Ryu, K. (2018). An assessment of the use of partial least squares structural equation modeling (PLS-SEM) in hospitality research. *International Journal of Contemporary Hospitality Management, 30*(1), 514-538.

Alter, G., & Gonzalez, R. (2018). Responsible practices for data sharing. *American Psychologist, 73*(2), 146.

Alvesson, M., & Spicer, A. (2019). Neo-institutional theory and organization studies: A mid-life crisis? *Organization Studies, 40*(2), 199-218.

Amann, R. I., Baichoo, S., Blencowe, B. J., Bork, P., Borodovsky, M., Brooksbank, C., . . . Danchin, A. (2019). Toward unrestricted use of public genomic data. *Science, 363*(6425), 350-352.

Andreoli-Versbach, P., & Mueller-Langer, F. (2014). Open access to data: An ideal professed but not practised. *Research Policy, 43*(9), 1621-1633.

Anjana, R., Pradeepa, R., Deepa, M., Datta, M., Sudha, V., Unnikrishnan, R., . . . Yajnik, C. (2011). Prevalence of diabetes and prediabetes (impaired fasting glucose and/or impaired glucose tolerance) in urban and rural India: Phase I results of the Indian Council of Medical Research–INdia DIABetes (ICMR–INDIAB) study. *Diabetologia, 54*(12), 3022-3027.

Anwar, R., Rehman, M., Wang, K. S., & Salleh, R. (2018). *Job Performance Through Knowledge Sharing Behavior in Global Software Development Organizations.* Paper presented at the 2018 Fourth International Conference on Information Retrieval and Knowledge Management (CAMP).

Arnold, J., Loan-Clarke, J., Coombs, C., Wilkinson, A., Park, J., & Preston, D. (2006). How well can the theory of planned behavior account for occupational intentions? *Journal of Vocational Behavior, 69*(3), 374-390.

as Reviwer, J. (2018). The Role of Contextual Factors in Knowledge Transfer in Transactional Projects. *International Journal of Management & Information Technology, 14*, 3301-3315.

Babbie, E. R. (2015). *The practice of social research*: Nelson Education.

Bada, M., Sasse, A. M., & Nurse, J. R. (2019). Cyber security awareness campaigns: Why do they fail to change behaviour? *arXiv preprint arXiv:1901.02672*.

Baraniuk, R. G. (2011). More is less: signal processing and the data deluge. *Science, 331*(6018), 717-719.

Barbosa, R. R. R., Sadre, R., Pras, A., & van de Meent, R. (2010). Simpleweb/university of twente traffic traces data repository. *Centre for Telematics and Information Technology, University of Twente*.

Bellé, N. (2013). Experimental evidence on the relationship between public service motivation and job performance. *Public Administration Review, 73*(1), 143-153.

Berge, Z. L., & Collins, M. P. (1995). *Computer mediated communication and the online classroom: distance learning*: Hampton press Cresskill.

Berman, F., & Cerf, V. (2013). Who will pay for public access to research data? *Science, 341*(6146), 616-617.

Bertagnolli, M. M., Sartor, O., Chabner, B. A., Rothenberg, M. L., Khozin, S., Hugh-Jones, C., . . . Murphy, M. J. (2017). Advantages of a truly open-access data-sharing model. In: Mass Medical Soc.

Bezuidenhout, L. (2013). Data sharing and dual-use issues. *Science and engineering ethics, 19*(1), 83-92.

Bezuidenhout, L., Kelly, A. H., Leonelli, S., & Rappert, B. (2017). '$100 Is Not Much To You': Open Science and neglected accessibilities for scientific research in Africa. *Critical Public Health, 27*(1), 39-49.

Bleize, D. N., & Antheunis, M. L. (2019). Factors influencing purchase intent in virtual worlds: a review of the literature. *Journal of Marketing Communications, 25*(4), 403-420.

Bloom, T., Ganley, E., & Winker, M. (2014). Data access for the open access literature: PLOS's data policy. In: Public Library of Science.

Bock, G.-W., Zmud, R. W., Kim, Y.-G., & Lee, J.-N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological factors, and organizational climate. *MIS quarterly, 29*(1), 87-111.

Bogers, M., Chesbrough, H., & Moedas, C. (2018). Open innovation: research, practices, and policies. *California Management Review, 60*(2), 5-16.

Bond – Lamberty, B. (2018). Data sharing and scientific impact in eddy covariance research. *Journal of Geophysical Research: Biogeosciences, 123*(4), 1440-1443.

Bonini, S., Eichler, H.-G., Wathion, N., & Rasi, G. (2014). Transparency and the European Medicines Agency—sharing of clinical trial data. *New England Journal of Medicine, 371*(26), 2452-2455.

Borgman, C., & Pasquetto, I. V. (2018). How and why do scientists reuse others' data to produce new knowledge?

Borgman, C. L. (2012). The conundrum of sharing research data. *Journal of the American Society for Information Science and Technology, 63*(6), 1059-1078.

Borgman, C. L. (2015). *Big data, little data, no data: Scholarship in the networked world*: MIT press.

Brink, H. I. (1993). Validity and reliability in qualitative research. *Curationis, 16*(2), 35-38.

Campbell, E. G., Weissman, J. S., Causino, N., & Blumenthal, D. (2000). Data withholding in academic medicine: characteristics of faculty denied access to research results and biomaterials. *Research Policy, 29*(2), 303-312.

Cao, Q. H., Giyyarpuram, M., Farahbakhsh, R., & Crespi, N. (2017). Policy-based usage control for a trustworthy data sharing platform in smart cities. *Future Generation Computer Systems*.

Carter, P., Laurie, G. T., & Dixon-Woods, M. (2015). The social licence for research: why care. data ran into trouble. *Journal of medical ethics, 41*(5), 404-409.

Cech, T. R., Eddy, S. R., Eisenberg, D., Hersey, K., Holtzman, S. H., Poste, G., . . . Waltham, M. C. (2003). Sharing publication-related data and materials: responsibilities of authorship in the life sciences. *Plant physiology, 132*(1), 19-24.

Check, J., & Schutt, R. K. (2012). Survey research. *Research methods in education*, 159-185.

Chen, F., Wang, S., Jiang, X., Ding, S., Lu, Y., Kim, J., . . . Wright, V. J. (2016). Princess: Privacy-protecting rare disease international network collaboration via encryption through software guard extensions. *Bioinformatics, 33*(6), 871-878.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464-504.

Chen, S. X., & Huang, T. M. (2007). Nonparametric estimation of copula functions for dependence modelling. *Canadian Journal of Statistics, 35*(2), 265-282.

Choi, S.-W. (2016). *New Explorations Into International Relations: Democracy, Foreign Investment, Terrorism, and Conflict* (Vol. 6): University of Georgia Press.

Cliggett, L. (2015). Preservation, sharing, and technological challenges of longitudinal research in the digital age. *eFieldnotes: the makings of anthropology in the digital world*, 231-250.

Cohen, M. A. (1988). Some new evidence on the seriousness of crime. *Criminology, 26*(2), 343-353.

Cooper, P. W. (2018). *Explosives engineering*: John Wiley & Sons.

Corti, L., Van den Eynden, V., Bishop, L., & Woollard, M. (2019). *Managing and sharing research data: a guide to good practice*: SAGE Publications Limited.

Cragin, M. H., Palmer, C. L., Carlson, J. R., & Witt, M. (2010). Data sharing, small science and institutional repositories. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 368*(1926), 4023-4038.

Creswell, J. W. (2011). Controversies in mixed methods research. *The Sage handbook of qualitative research, 4*, 269-284.

Curty, R., Yoon, A., Jeng, W., & Qin, J. (2016). *Untangling data sharing and reuse in social sciences.* Paper presented at the Proceedings of the 79th ASIS&T Annual Meeting: Creating Knowledge, Enhancing Lives Through Information & Technology.

Curty, R. G. (2015). Beyond "Data Thrifting": An Investigation of Factors Influencing Research Data Reuse In the Social Sciences.

Curty, R. G. (2016). Factors influencing research datafire-‒use in Social Sciences: An exploratory study.

Dai, S. Q., Li, H., Xiong, J., Ma, J., Guo, H. Q., Xiao, X., & Zhao, B. (2018). Assessing the extent and impact of online data sharing in eddy covariance flux research. *Journal of Geophysical Research: Biogeosciences, 123*(1), 129-137.

Davies, T., & Perini, F. (2016). Researching the emerging impacts of open data: revisiting the ODDC conceptual framework. *The Journal of Community Informatics, 12*(2).

Denzin, N. K., & Giardina, M. D. (2018). *Qualitative inquiry in the public sphere*: Routledge.

Destro Bisol, G., Anagnostou, P., Capocasa, M., Bencivelli, S., Cerroni, A., Contreras, J. L., . . . Heeney, C. (2014). Perspectives on Open Science and scientific data sharing: an interdisciplinary workshop.

Dimachki, M. E. (2019). More data and more data sharing: Navigating an open banking world. *Journal of Digital Banking, 3*(3), 206-214.

Doherty, J., Gourvenec, S., Gaone, F., Pineda, J., Kelly, R., O'Loughlin, C., . . . Sloan, S. (2018). A novel web based application for storing, managing and sharing geotechnical data, illustrated using the National Soft Soil Field Testing Facility in Ballina, Australia. *Computers and Geotechnics, 93*, 3-8.

Doshi, P., Jefferson, T., & Del Mar, C. (2012). The imperative to share clinical study reports: recommendations from the Tamiflu experience. *PLoS medicine, 9*(4), e1001201.

Dowell, J., Cleland, J., Fitzpatrick, S., McManus, C., Nicholson, S., Oppé, T., . . . Thornton, S. (2018). The UK medical education database (UKMED) what is it? Why and how might you use it? *BMC medical education, 18*(1), 6.

Dreyfus, J. C., & Sobel, M. E. (2018). Concern about justifying the release of genomic data as a civil right. *The American Journal of Human Genetics, 103*(1), 163-165.

Duerr, S., Holotiuk, F., Wagner, H.-T., Beimborn, D., & Weitzel, T. (2018). *What is digital organizational culture? Insights from exploratory case studies.* Paper presented at the Proceedings of the 51st Hawaii International Conference on System Sciences.

Eastin, M. S., Brinson, N. H., Doorey, A., & Wilcox, G. (2016). Living in a big data world: Predicting mobile commerce activity through privacy concerns. *Computers in Human Behavior, 58*, 214-220.

Eastwood, J. D., & Smilek, D. (2005). Functional consequences of perceiving facial expressions of emotion without awareness. *Consciousness and cognition, 14*(3), 565-584.

Ebrahim, S., Sohani, Z. N., Montoya, L., Agarwal, A., Thorlund, K., Mills, E. J., & Ioannidis, J. P. (2014). Reanalyses of randomized clinical trial data. *Jama, 312*(10), 1024-1032.

Ellaway, R. H., Pusic, M. V., Galbraith, R. M., & Cameron, T. (2014). Developing the role of big data and analytics in health professional education. *Medical teacher, 36*(3), 216-222.

Elliott, K. C., Cheruvelil, K. S., Montgomery, G. M., & Soranno, P. A. (2016). Conceptions of good science in our data-rich world. *BioScience, 66*(10), 880-889.

Faniel, I. M., & Yakel, E. (2011). Significant properties as contextual metadata. *Journal of Library Metadata, 11*(3-4), 155-165.

Farber, G. K. (2017). Can data repositories help find effective treatments for complex diseases? *Progress in neurobiology, 152*, 200-212.

Fortunato, A., Grainger, D. W., & Abou-El-Enein, M. (2018). Enhancing patient-level clinical data access to promote evidence-based practice and incentivize therapeutic innovation. *Advanced drug delivery reviews, 136*, 97-104.

Foster, E. D., & Deardorff, A. (2017). Open science framework (OSF). *Journal of the Medical Library Association: JMLA, 105*(2), 203.

Fraenkel, J., & Wallen, W. (2000). How to design and evaluate educational research. In: New York, NY: McGraw Hill.

Frank, R. D., Kriesberg, A., Yakel, E., & Faniel, I. M. (2015). *Looting hoards of gold and poaching spotted owls: data confidentiality among archaeologists & zoologists.* Paper presented at the Proceedings of the 78th ASIS&T Annual Meeting: Information Science with Impact: Research in and for the Community.

Garson, D. (2008). Factor Analysis: Statnotes. Retrieved March 22, 2008, from North Carolina State University Public Administration Program. In.

Gewin, V. (2016). Data sharing: An open mind on open data. *Nature, 529*(7584), 117-119.

Gold, J. A., Rimal, B., Nolan, A., & Nelson, L. S. (2007). A strategy of escalating doses of benzodiazepines and phenobarbital administration reduces the need for mechanical ventilation in delirium tremens. *Critical care medicine, 35*(3), 724.

Gonzalez, A., & Peres-Neto, P. R. (2015). Data curation: Act to staunch loss of research data. *Nature, 520*(7548), 436.

Grand, A., Wilkinson, C., Bultitude, K., & Winfield, A. F. (2016). Mapping the hinterland: Data issues in open science. *Public Understanding of Science, 25*(1), 88-103.

Gregory, K., Cousijn, H., Groth, P., Scharnhorst, A., & Wyatt, S. (2018). Understanding data retrieval practices: A social informatics perspective. *arXiv preprint arXiv:1801.04971*.

Greve, H. R., & Teh, D. (2018). Goal selection internally and externally: A behavioral theory of institutionalization. *International Journal of Management Reviews, 20*, S19-S38.

Groves, R. M. (2018). The promise of collaborative data sharing across research sectors. In *The Palgrave Handbook of Survey Research* (pp. 297-300): Springer.

Guo, Y., Xu, G., Yang, X., Ruan, K., Ma, T., Zhang, Q., . . . Guo, Z. (2018). Significantly enhanced and precisely modeled thermal conductivity in polyimide nanocomposites with chemically modified graphene via in situ polymerization and electrospinning-hot press technology. *Journal of Materials Chemistry C, 6*(12), 3004-3015.

Haeussler, C. (2011). Information-sharing in academia and the industry: A comparative study. *Research Policy, 40*(1), 105-122.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. *Journal of the academy of marketing science, 45*(5), 616-632.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice, 19*(2), 139-152.

Hair Jr, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced issues in partial least squares structural equation modeling*: Sage Publications.

Hall, N. F. (2013). *Environmental studies faculty attitudes towards sharing of research data.* Paper presented at the Proceedings of the 13th ACM/IEEE-CS joint conference on Digital libraries.

Hall, P. (2013). *The bootstrap and Edgeworth expansion*: Springer Science & Business Media.

Harrison, J. S., Boivie, S., Sharp, N. Y., & Gentry, R. J. (2018). Saving face: How exit in response to negative press and star analyst downgrades reflects reputation maintenance by directors. *Academy of Management Journal, 61*(3), 1131-1157.

Hendler, J. (2014). Data integration for heterogenous datasets. *Big data, 2*(4), 205-215.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*(1), 115-135.

Hesse, B. W. (2018). Can psychology walk the walk of open science? *American Psychologist, 73*(2), 126.

Higgins, J., & Green, S. (2018). Cochrane Handbook for Systematic Reviews of Interventions Version 5.1. 0 (2013). In.

Hina, S., Selvam, D. D. D. P., & Lowry, P. B. (2019). Institutional governance and protection motivation: Theoretical insights into shaping employees' security compliance behavior in higher education institutions in the developing world. *Computers & Security, 87*, 101594.

Holdren, J. P. (2013). Increasing access to the results of federally funded scientific research. *Office of Science and Technology Policy, Executive Office of the President*.

Holsapple, C. W., & Joshi, K. D. (2004). A formal knowledge management ontology: Conduct, activities, resources, and influences. *Journal of the American Society for Information Science and Technology, 55*(7), 593-612.

Hoogervorst, J., van der Flier, H., & Koopman, P. (2004). Implicit communication in organisations: The impact of culture, structure and management practices on employee behaviour. *Journal of managerial psychology, 19*(3), 288-311.

Horton, L., & Katsanidou, A. (2011). Purposing your survey. *IASSIST Quarterly, 35*(4).

Hossain, M. (2015). A review of literature on open innovation in small and medium-sized enterprises. *Journal of Global Entrepreneurship Research, 5*(1), 6.

Hossain, M., & Kim, M. (2018). Does Multidimensional Service Quality Generate Sustainable Use Intention for Facebook? *Sustainability, 10*(7), 2283.

Houtkoop, B. L., Chambers, C., Macleod, M., Bishop, D. V., Nichols, T. E., & Wagenmakers, E.-J. (2018). Data sharing in psychology: A survey on barriers and preconditions. *Advances in Methods and Practices in Psychological Science, 1*(1), 70-85.

Hsu, C.-L., & Lin, J. C.-C. (2008). Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Information & management, 45*(1), 65-74.

Hsu, L., Martin, R. L., McElroy, B., Litwin-Miller, K., & Kim, W. (2015). Data management, sharing, and reuse in experimental geomorphology: Challenges, strategies, and scientific opportunities. *Geomorphology, 244*, 180-189.

Huang, F., Teo, T., Sánchez-Prieto, J. C., García-Peñalvo, F. J., & Olmos-Migueláñez, S. (2019). Cultural values and technology adoption: A model comparison with university teachers from China and Spain. *Computers & Education, 133*, 69-81.

Huang, X., Hawkins, B. A., & Qiao, G. (2013). Biodiversity data sharing: Will peer-reviewed data papers work? *BioScience, 63*(1), 5-6.

Iqbal, S. A., Wallach, J. D., Khoury, M. J., Schully, S. D., & Ioannidis, J. P. (2016). Reproducible research practices and transparency across the biomedical literature. *PLoS biology, 14*(1), e1002333.

Irawan, D. E., & Rachmi, C. N. (2018). Promoting data sharing among Indonesian scientists: A proposal of generic university-level RDMP.

Jacob, S. A., & Furgerson, S. P. (2012). Writing interview protocols and conducting interviews: Tips for students new to the field of qualitative research. *The qualitative report, 17*(42), 1-10.

Jacobsen, C. B., Hvitved, J., & Andersen, L. B. (2014). Command and motivation: How the perception of external interventions relates to intrinsic motivation and public service motivation. *Public Administration, 92*(4), 790-806.

James, T. L., Wallace, L., Warkentin, M., Kim, B. C., & Collignon, S. E. (2017). Exposing others' information on online social networks (OSNs): Perceived shared risk, its determinants, and its influence on OSN privacy control use. *Information & management, 54*(7), 851-865.

Janssen, M., Charalabidis, Y., & Zuiderwijk, A. (2012). Benefits, adoption barriers and myths of open data and open government. *Information systems management, 29*(4), 258-268.

Joel, S., Eastwick, P. W., & Finkel, E. J. (2018). Open sharing of data on close relationships and other sensitive social psychological topics: Challenges, tools, and future directions. *Advances in Methods and Practices in Psychological Science, 1*(1), 86-94.

Jones, M. C., Cline, M., & Ryan, S. (2006). Exploring knowledge sharing in ERP implementation: an organizational culture framework. *Decision Support Systems, 41*(2), 411-434.

Kian, T. S., & Yusoff, W. F. W. (2015). Motivation and Promotion Opportunity of Academic Citizens towards Open Innovation: Proposed Model. *Procedia-Social and Behavioral Sciences, 204*, 29-35.

Kiernan, V. (2016). *The duel in European history: honour and the reign of aristocracy*: Zed Books Ltd.

Kim, J., Lee, C., & Elias, T. (2015). Factors affecting information sharing in social networking sites amongst university students: Application of the knowledge-sharing model to social networking sites. *Online Information Review, 39*(3), 290-309.

Kim, J., Yoon, Y., & Zo, H. (2015). *Why People Participate in the Sharing Economy: A Social Exchange Perspective.* Paper presented at the PACIS.

Kim, Y. (2017). Fostering scientists' data sharing behaviors via data repositories, journal supplements, and personal communication methods. *Information Processing & Management, 53*(4), 871-885.

Kim, Y., & Adler, M. (2015). Social scientists' data sharing behaviors: Investigating the roles of individual motivations, institutional pressures, and data repositories. *International journal of information management, 35*(4), 408-418.

Kim, Y., & Nah, S. (2018). Internet researchers' data sharing behaviors: An integration of data reuse experience, attitudinal beliefs, social norms, and resource factors. *Online Information Review, 42*(1), 124-142.

Kim, Y., & Stanton, J. M. (2012). Institutional and individual influences on scientists' data sharing practices. *Journal of Computational Science Education, 3*(1), 47-56.

Kim, Y., & Stanton, J. M. (2013). *Institutional and individual influences on scientists' data sharing behaviors: A multilevel analysis.* Paper presented at the Proceedings of the 76th ASIS&T Annual Meeting: Beyond the Cloud: Rethinking Information Boundaries.

Kim, Y., & Stanton, J. M. (2016). Institutional and individual factors affecting scientists' data – sharing behaviors: A multilevel analysis. *Journal of the Association for Information Science and Technology, 67*(4), 776-799.

Kindling, M., Fütterer, H.-A., Sandt, S. v. d., & Petrus, A. (2014). iConference 2014 Proceedings Documentation.

King, G. (2014). Restructuring the social sciences: reflections from Harvard's Institute for Quantitative Social Science. *PS: Political Science & Politics, 47*(1), 165-172.

Kirkeboen, L. J., Leuven, E., & Mogstad, M. (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics, 131*(3), 1057-1111.

Kitchin, R., & Lauriault, T. P. (2015). Small data in the era of big data. *GeoJournal, 80*(4), 463-475.

Knoppers, B. M., Harris, J. R., Tassé, A. M., Budin-Ljøsne, I., Kaye, J., Deschênes, M., & Ma'n, H. Z. (2011). Towards a data sharing Code of Conduct for international genomic research. *Genome medicine, 3*(7), 46.

Kodama, Y., Shumway, M., & Leinonen, R. (2011). The Sequence Read Archive: explosive growth of sequencing data. *Nucleic acids research, 40*(D1), D54-D56.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science, 3*(3), 383-397.

Komolafe-Opadeji, H. (2011). A ten-year descriptive review of book acquisitions trends, challenges, and current issues in a Nigerian Medical School Library. *Library Philosophy and Practice*, 1.

Kopko, K. C., Edwards, A., Krause, E., & McGonigle, V. J. (2016). Assessing Outcomes of National Science Foundation Grants in the Social Sciences. *Council on Undergraduate Research Quarterly, 36*(3).

Kostova, T., & Marano, V. (2019). Institutional theory perspectives on emerging markets. In *The Oxford Handbook of Management in Emerging Markets* (pp. 99): Oxford University Press.

Kothari, C. R. (2004). *Research methodology: Methods and techniques*: New Age International.

Kotrlik, J., & Higgins, C. (2001). Organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. *Information technology, learning, and performance journal, 19*(1), 43.

Kratz, J. E., & Strasser, C. (2015). Researcher perspectives on publication and peer review of data. *PloS one, 10*(2), e0117619.

Kwak, M., & Kim, H. (2017). Green profit maximization through integrated pricing and production planning for a line of new and remanufactured products. *Journal of cleaner production, 142*, 3454-3470.

Labastida, I. (2015). The time has come for managing and sharing research data in universities. *Journal of Science Communication, 14*(4), C03.

Lai, R. Y. (2010). System and method for generating Web Service architectures using a Web Services structured methodology. In: Google Patents.

Landor, A., & Barr, A. (2018). Politics of respectability, colorism, and the terms of social exchange in family research. *Journal of family theory & review, 10*(2), 330-347.

Leonelli, S., Spichtinger, D., & Prainsack, B. (2015). Sticks and carrots: encouraging open science at its source. *Geo: geography and environment, 2*(1), 12-16.

Li, Y., & Tschirhart, L. (2012). Preparing To support research data sharing. *Special issues in data management, 1110*, 145-162.

Lilienfeld, S. O. (2017). Psychology's replication crisis and the grant culture: Righting the ship. *Perspectives on Psychological Science, 12*(4), 660-664.

Linek, S. B., Fecher, B., Friesike, S., & Hebing, M. (2017). Data sharing as social dilemma: Influence of the researcher's personality. *PloS one, 12*(8), e0183216.

Locke, E. A., & Schattke, K. (2018). Intrinsic and extrinsic motivation: Time for expansion and clarification. *Motivation Science*.

Lyon, L. (2016). Transparency: the emerging third dimension of Open Science and Open Data. *Liber quarterly, 25*(4).

MacMillan, D. (2014). Data sharing and discovery: What librarians need to know. *The Journal of Academic Librarianship, 40*(5), 541-549.

Madas, B. G., & Schofield, P. N. (2018). Survey on data management in radiation protection research. *Radiation protection dosimetry, 183*(1-2), 233-236.

Majeed, R. (2012). Disseminating The Power Of Information: Kenya Open Data Initiative, 2011–2012. *Innovations for Successful Societies*.

Majrashi, K., Hamilton, M., & Uitdenbogerd, A. L. (2015). *Multiple user interfaces and cross-platform user experience: Theoretical foundations.* Paper presented at the Proceedings of the Fifth International Conference on Computer Science, Engineering and Applications (CCSEA-2015). AIRCC Publishing Corporation.

Marcial, L. H., & Hemminger, B. M. (2010). Scientific data repositories on the Web: An initial survey. *Journal of the American Society for Information Science and Technology, 61*(10), 2029-2048.

Marcoulides, G. A., & Heck, R. H. (1993). Organizational culture and performance: Proposing and testing a model. *Organization science, 4*(2), 209-225.

Martone, M. E., Garcia-Castro, A., & VandenBos, G. R. (2018). Data sharing in psychology. *American Psychologist, 73*(2), 111.

Masa'deh, R. e., Obeidat, B. Y., & Tarhini, A. (2016). A Jordanian empirical study of the associations among transformational leadership, transactional leadership, knowledge sharing, job performance, and firm performance: A structural equation modelling approach. *Journal of Management Development, 35*(5), 681-705.

McGee, R., & Edwards, D. (2016). Introduction: Opening governance–Change, continuity and conceptual ambiguity.

McGuire, A. L., Hamilton, J. A., Lunstroth, R., McCullough, L. B., & Goldman, A. (2008). DNA data sharing: research participants' perspectives. *Genetics in Medicine, 10*(1), 46.

Mennes, M., Biswal, B. B., Castellanos, F. X., & Milham, M. P. (2013). Making data sharing work: the FCP/INDI experience. *Neuroimage, 82*, 683-691.

Meyer, M. N. (2018). Practical tips for ethical data sharing. *Advances in Methods and Practices in Psychological Science, 1*(1), 131-144.

Miguel, E., Camerer, C., Casey, K., Cohen, J., Esterling, K. M., Gerber, A., . . . Imbens, G. (2014). Promoting transparency in social science research. *Science, 343*(6166), 30-31.

Miltgen, C. L., & Peyrat-Guillard, D. (2014). Cultural and generational influences on privacy concerns: a qualitative study in seven European countries. *European Journal of Information Systems, 23*(2), 103-125.

Mish, F. C. (2004). *Merriam-Webster's collegiate dictionary*: Merriam-Webster.

Mojdeh, S., Head, M., & El Shamy, N. (2018). Knowledge sharing in social networking sites: how context impacts individuals' social and intrinsic motivation to contribute in online communities. *AIS Transactions on Human-Computer Interaction, 10*(2), 82-104.

Monforton, C. (2006). Weight of the evidence or wait for the evidence? Protecting underground miners from diesel particulate matter. *American Journal of Public Health, 96*(2), 271-276.

Mons, B., Neylon, C., Velterop, J., Dumontier, M., da Silva Santos, L. O. B., & Wilkinson, M. D. (2017). Cloudy, increasingly FAIR; revisiting the FAIR Data guiding principles for the European Open Science Cloud. *Information Services & Use, 37*(1), 49-56.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research, 2*(3), 192-222.

Morris, J., Marzano, M., Dandy, N., & O'Brien, L. (2012). Theories and models of behaviour and behaviour change. *Forest Research: Surrey, United Kingdom*.

Moss, E., Cave, C., & Lyle, J. (2015). Sharing and citing research data: A repository's perspective. In: West Academic Publishing.

Mueller-Langer, F., & Andreoli-Versbach, P. (2018). Open access to research data: Strategic delay and the ambiguous welfare effects of mandatory data disclosure. *Information Economics and Policy, 42*, 20-34.

Mueller-Langer, F., & Watt, R. (2014). The hybrid open access citation advantage: how many more cites is a $3,000 fee buying you? *Published as How Many More Cites is a $3,000 Open Access Fee Buying You*, 931-954.

Mumby, D. K. (1988). *Communication and power in organizations: Discourse, ideology, and domination*: Ablex Pub.

Munafò, M. R., Nosek, B. A., Bishop, D. V., Button, K. S., Chambers, C. D., Du Sert, N. P., . . . Ioannidis, J. P. (2017). A manifesto for reproducible science. *Nature human behaviour, 1*(1), 0021.

Naudet, F., Sakarovitch, C., Janiaud, P., Cristea, I., Fanelli, D., Moher, D., & Ioannidis, J. P. (2018). Data sharing and reanalysis of randomized controlled trials in leading biomedical journals with a full data sharing policy: survey of studies published in The BMJ and PLOS Medicine. *bmj, 360*, k400.

Neuman, W. L., & Kreuger, L. (2003). *Social work research methods: Qualitative and quantitative approaches*: Allyn and Bacon.

Norman, T. R. (2018). Procedurally specifying calculated database fields, and populating them. In: Google Patents.

Nosek, B. A., Alter, G., Banks, G. C., Borsboom, D., Bowman, S. D., Breckler, S. J., . . . Christensen, G. (2015). Promoting an open research culture. *Science, 348*(6242), 1422-1425.

Ogba, O. C. (2014). The practicality of resource sharing in academic law libraries in South-western Nigeria. *Library Philosophy and Practice*, 0_1.

Olson, S., & Downey, A. (2016). *Sharing clinical research data: workshop summary. 2013.* Paper presented at the Book Sharing Clinical Research Data: Workshop Summary. 2013.

Oppenheim, A. N. (1992). Questionnaire design. *Interviewing and Attitude measurement, 24*.

Pampel, H., Vierkant, P., Scholze, F., Bertelmann, R., Kindling, M., Klump, J., . . . Dierolf, U. (2013). Making research data repositories visible: the re3data. org registry. *PloS one, 8*(11), e78080.

Park, H., & Wolfram, D. (2017). An examination of research data sharing and re-use: implications for data citation practice. *Scientometrics, 111*(1), 443-461.

Park, J., & Gabbard, J. L. (2018). Factors that affect scientists' knowledge sharing behavior in health and life sciences research communities: differences between explicit and implicit knowledge. *Computers in Human Behavior, 78*, 326-335.

Paxton, A., & Tullett, A. (2019). Open Science in Data-Intensive Psychology and Cognitive Science. *Policy Insights from the Behavioral and Brain Sciences, 6*(1), 47-55.

Pitrelli, N., & Arabito, S. (2015). Open Science training and education: challenges and difficulties on the researchers' side and in public engagement. *Journal of Science Communication, 14*(4), C01.

Pitt, M. A., & Tang, Y. (2013). What should be the data sharing policy of cognitive science? *Topics in cognitive science, 5*(1), 214-221.

Piwowar, H. A., & Vision, T. J. (2013). Data reuse and the open data citation advantage. *PeerJ, 1*, e175.

Platt, J. E., Jacobson, P. D., & Kardia, S. L. (2018). Public Trust in Health Information Sharing: A measure of system trust. *Health services research, 53*(2), 824-845.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual review of psychology, 63*, 539-569.

Powell, W., & Di Maggio, P. (1983). Institutionnalism Isomorphisme and Collective Rationality. *American Sociological Review, 48*.

Ramgutty-Wong, A., & Dusoye, I. (2011). *Assessing cultural adaptation competencies at senior executive level: The case of expatriates in Mauritius.* Paper presented at the International Conference on International Trade and Investment, Mauritius.

Ramjoué, C. (2015). Towards open science: The vision of the European Commission. *Information Services & Use, 35*(3), 167-170.

Razak, N. A., Pangil, F., Zin, M. L. M., Yunus, N. A. M., & Asnawi, N. H. (2016). Theories of knowledge sharing behavior in business strategy. *Procedia Economics and Finance, 37*, 545-553.

Recker, J., Zenk-Möltgen, W., & Mauer, R. (2017). Applications of Research Data Management at GESIS Data Archive for the Social Sciences. *Research Data Management-A European Perspective. Berlin, Boston: De Gruyter, S*, 119-146.

Reichert, B. E., & Sohn, M. (2019). The Hidden Cost of Competition: The Effect of Competition for Monetary Rewards and Social Recognition on Psychological Pressure and Knowledge Sharing. *Available at SSRN 3219853*.

Reichman, O. J., Jones, M. B., & Schildhauer, M. P. (2011). Challenges and opportunities of open data in ecology. *Science, 331*(6018), 703-705.

Roberts, E., Anderson, B. A., Skerratt, S., & Farrington, J. (2017). A review of the rural-digital policy agenda from a community resilience perspective. *Journal of Rural Studies, 54*, 372-385.

Robinson – García, N., Jiménez – Contreras, E., & Torres – Salinas, D. (2016). Analyzing data citation practices using the data citation index. *Journal of the Association for Information Science and Technology, 67*(12), 2964-2975.

Robinson, R. S. (2014). Purposive sampling. *Encyclopedia of Quality of Life and Well-Being Research*, 5243-5245.

Ross, M. W., Iguchi, M. Y., & Panicker, S. (2018). Ethical aspects of data sharing and research participant protections. *American Psychologist, 73*(2), 138.

Rowhani-Farid, A., Allen, M., & Barnett, A. G. (2017). What incentives increase data sharing in health and medical research? A systematic review. *Research integrity and peer review, 2*(1), 4.

Sandve, G. K., Nekrutenko, A., Taylor, J., & Hovig, E. (2013). Ten simple rules for reproducible computational research. In: Public Library of Science.

Savage, C. J., & Vickers, A. J. (2009). Empirical study of data sharing by authors publishing in PLoS journals. *PloS one, 4*(9), e7078.

Sayogo, D. S., & Pardo, T. A. (2011). *Understanding the capabilities and critical success factors in collaborative data sharing network: The case of DataONE.* Paper presented at the Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times.

Sayre, F., & Riegelman, A. (2018). The reproducibility crisis and academic libraries. *College & Research Libraries, 79*(1), 2.

Scaramozzino, J. M., Ramírez, M. L., & McGaughey, K. J. (2012). A study of faculty data curation behaviors and attitudes at a teaching-centered university. *College & Research Libraries, 73*(4), 349-365.

Schein, E. H. (1990). *Organizational culture* (Vol. 45): American Psychological Association.

Scheliga, K., & Friesike, S. (2014). Putting open science into practice: A social dilemma? *First Monday, 19*(9).

Schmidt, T., Philipsen, R., Themann, P., & Ziefle, M. (2016). *Public perception of V2X-technology-evaluation of general advantages, disadvantages and reasons for data sharing with connected vehicles.* Paper presented at the 2016 IEEE Intelligent Vehicles Symposium (IV).

Scott, W. R. (2005). Institutional theory: Contributing to a theoretical research program. *Great minds in management: The process of theory development, 37*(2005), 460-484.

Shah, D. V., Cappella, J., & Neuman, W. R. (2015). Toward computational social science: Exploiting big data in the digital age. *Philadelphia PA: The ANNALS of the American Academy of Political and Social Science*.

Shen, Y. (2016). Research data sharing and reuse practices of academic faculty researchers: A Study of the Virginia Tech Data Landscape. *International Journal of Digital Curation, 10*(2), 157-175.

Shen, Y. (2018). Data sharing practices, information exchange behaviors, and knowledge discovery dynamics: a study of natural resources and environmental scientists. *Environmental Systems Research, 6*(1), 9.

Si, L., Xing, W., Zhuang, X., Hua, X., & Zhou, L. (2015). Investigation and analysis of research data services in university libraries. *The Electronic Library, 33*(3), 417-449.

Soranno, P. A., Bissell, E. G., Cheruvelil, K. S., Christel, S. T., Collins, S. M., Fergus, C. E., . . . Oliver, S. K. (2015). Building a multi-scaled geospatial temporal ecology database from disparate data sources: fostering open science and data reuse. *GigaScience, 4*(1), s13742-13015-10067-13744.

Spallek, H., Weinberg, S., Manz, M., Nanayakkara, S., Zhou, X., & Johnson, L. (2019). Perceptions and Attitudes toward Data Sharing among Dental Researchers. *JDR Clinical & Translational Research, 4*(1), 68-75.

Srikanthan, S., Dwarkadas, S., & Shen, K. (2015). *Data sharing or resource contention: Toward performance transparency on multicore systems.* Paper presented at the 2015 {USENIX} Annual Technical Conference ({USENIX}{ATC} 15).

Stephens, D. C. (2015). Large-scale data storage and delivery system. In: Google Patents.

Stevenson, A. (2010). *Oxford dictionary of English*: Oxford University Press, USA.

Sun, Y., Jiang, H., Hwang, Y., & Shin, D. (2018). Why should I share? An answer from personal information management and organizational citizenship behavior perspectives. *Computers in Human Behavior, 87*, 146-154.

Tabachnick, B. G., & Fidell, L. S. (2001). Principal components and factor analysis. *Using multivariate statistics, 4*, 582-633.

Takashima, K., Maru, Y., Mori, S., Mano, H., Noda, T., & Muto, K. (2018). Ethical concerns on sharing genomic data including patients' family members. *BMC medical ethics, 19*(1), 61.

Tannenbaum, S., Ross, J. S., Krumholz, H. M., Desai, N. R., Ritchie, J. D., Lehman, R., . . . Groves, T. (2018). Early experiences with journal data sharing policies: a survey of published clinical trial investigators. *Annals of internal medicine*.

Taylor, R., & Kelsey, T. (2016). *Transparency and the open society: Practical lessons for effective policy*: Policy Press.

Tenenhaus, M. (2008). Component-based structural equation modelling. *Total quality management, 19*(7-8), 871-886.

Tenopir, C., Allard, S., Douglass, K., Aydinoglu, A. U., Wu, L., Read, E., . . . Frame,M. (2011). Data sharing by scientists: practices and perceptions. *PloS one, 6*(6), e21101.

Tenopir, C., Dalton, E. D., Allard, S., Frame, M., Pjesivac, I., Birch, B., . . . Dorsett, K. (2015). Changes in data sharing and data reuse practices and perceptions among scientists worldwide. *PloS one, 10*(8), e0134826.

Toelch, U., & Ostwald, D. (2018). Digital open science—Teaching digital tools for reproducible and transparent research. *PLoS biology, 16*(7), e2006022.

Triola, M. M., Hawkins, R. E., & Skochelak, S. E. (2018). The time is now: Using graduates' practice data to drive medical education reform. *Academic Medicine, 93*(6), 826-828.

Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information technology theory and application, 11*(2), 5-40.

Van den Eynden, V., & Corti, L. (2017). Advancing research data publishing practices for the social sciences: from archive activity to empowering researchers. *International Journal on Digital Libraries, 18*(2), 113-121.

Velten, L., & Lashley, C. (2018). The meaning of cultural diversity among staff as it pertains to employee motivation. *Research in Hospitality Management, 7*(2), 105-113.

Verma, V. K., & Chandra, B. (2018). An application of theory of planned behavior to predict young Indian consumers' green hotel visit intention. *Journal of cleaner production, 172*, 1152-1162.

Vicente-Sáez, R., & Martínez-Fuentes, C. (2018). Open Science now: A systematic literature review for an integrated definition. *Journal of business research, 88*, 428-436.

Vickers, A. J. (2011). Making raw data more widely available. In: British Medical Journal Publishing Group.

Vitak, J., Shilton, K., & Ashktorab, Z. (2016). *Beyond the Belmont principles: Ethical challenges, practices, and beliefs in the online data research community.* Paper presented at the Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing.

Vogel, P., Greiser, T., & Mattfeld, D. C. (2011). Understanding bike-sharing systems using data mining: Exploring activity patterns. *Procedia-Social and Behavioral Sciences, 20*, 514-523.

Wallach, J. D., Boyack, K. W., & Ioannidis, J. P. (2018). Reproducible research practices, transparency, and open access data in the biomedical literature, 2015–2017. *PLoS biology, 16*(11), e2006930.

Wallis, J. C., Rolando, E., & Borgman, C. L. (2013). If we share data, will anyone use them? Data sharing and reuse in the long tail of science and technology. *PloS one, 8*(7), e67332.

Wang, G., Wei, Y., Qiao, S., Lin, P., & Chen, Y. (2018). *Generalized inverses: theory and computations* (Vol. 53): Springer.

Wang, Y., Xiang, D., Yang, Z., & Ma, S. S. (2019). Unraveling customer sustainable consumption behaviors in sharing economy: A socio-economic approach based on social exchange theory. *Journal of cleaner production, 208*, 869-879.

Weber, N. M., Piwowar, H. A., & Vision, T. J. (2010). Evaluating data citation and sharing policies in the environmental sciences. *Proceedings of the American Society for Information Science and Technology, 47*(1), 1-2.

Wilkinson, D., Harries, G., Thelwall, M., & Price, L. (2003). Motivations for academic Web site interlinking: Evidence for the Web as a novel source of information on informal scholarly communication. *Journal of Information Science, 29*(1),49-56.

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., . . . Bourne, P. E. (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Scientific data, 3*.

Williams, E. S., Manwell, L. B., Konrad, T. R., & Linzer, M. (2007). The relationship of organizational culture, stress, satisfaction, and burnout with physician-reported error and suboptimal patient care: results from the MEMO study. *Health care management review, 32*(3), 203-212.

Willinsky, J. (2018). Scholarly associations and the economic viability of open access publishing. *Demonstration Journal of the Health Sciences Theme, 1*(2).

Wipperman, S. L., Martin, S., & Bowley, C. (2018). Balancing influence in a shifting scholarly communication landscape: creating library-owned, community-aligned infrastructure through individual, local, and community action. *College & Research Libraries News, 79*(5), 244.

Wouters, P. (2002). *Policies on digital research data: An international survey*: Niwi-Knaw.

Wu, P. C., & Wang, Y.-C. (2011). The influences of electronic word-of-mouth message appeal and message source credibility on brand attitude. *Asia Pacific Journal of Marketing and Logistics, 23*(4), 448-472.

Wynholds, L., Fearon Jr, D. S., Borgman, C. L., & Traweek, S. (2011). *When use cases are not useful: Data practices, astronomy, and digital libraries.* Paper presented at the Proceedings of the 11th annual international ACM/IEEE joint conference on Digital libraries.

Yang, J.-J., Li, J.-Q., & Niu, Y. (2015). A hybrid solution for privacy preserving medical data sharing in the cloud environment. *Future Generation Computer Systems, 43*, 74-86.

Yang, S., Wu, F., Tang, S., Gao, X., Yang, B., & Chen, G. (2017). On designing data quality-aware truth estimation and surplus sharing method for mobile crowdsensing. *IEEE Journal on Selected Areas in Communications, 35*(4), 832-847.

Zellweger, T. M., Chrisman, J. J., Chua, J. H., & Steier, L. P. (2019). Social structures, social relationships, and family firms. In: Sage Publications Sage CA: Los Angeles, CA.

Zenk-Möltgen, W., Akdeniz, E., Katsanidou, A., Naßhoven, V., & Balaban, E. (2018). Factors influencing the data sharing behavior of researchers in sociology and political science. *Journal of Documentation, 74*(5), 1053-1073.

Zenk-Möltgen, W., & Lepthien, G. (2014). Data sharing in sociology journals. *Online Information Review, 38*(6), 709-722.

Zhao, E.-L., Hao, W.-N., Zhao, S.-N., & Han, X.-Y. (2010). Improved Situation Clustering Display Algorithm Based on Density Method [J]. *Computer Engineering, 18*.

Ziefle, M., Halbey, J., & Kowalewski, S. (2016). *Users' Willingness to Share Data on the Internet: Perceived Benefits and Caveats.* Paper presented at the IoTBD.