

**A THEORETICAL MODEL FOR BIG DATA ADOPTION IN THE
HIGHER EDUCATION INSTITUTION OF PAKISTAN**

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**FACULTY OF COMPUTER SCIENCE AND INFORMATION
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KUALA LUMPUR**

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A THEORETICAL MODEL FOR BIG DATA ADOPTION IN THE HIGHER EDUCATION INSTITUTION OF PAKISTAN

ABSTRACT

Big data adoption has already gained tremendous attention from executives in various fields. However, it is still not well explored in the education sector, where a large amount of academic data is being produced. The higher education institutions of Pakistan are facing difficulties in upgrading the educational managerial competency that is needed to fulfil future demands. Thus, there is a need of big data adoption in higher education institutions of Pakistan to improve the managerial aptitude. However, there is a limited literature on theoretical model and factors that affect big data adoption in the higher education institutions. This study aims to develop a theoretical model and identify the factors that influence big data adoption in a higher education institution. Ten factors were identified from the literature, and a theoretical model was developed. Technology-Organization-Environment and Diffusion of Innovation theories were adopted as a theoretical base in this study. Meanwhile, the moderating effects of the university size and university age on big data adoption were added to the developed model. A virtual university in Pakistan is recognized by the Higher Education Commission of Pakistan as a higher education institution is chosen. Data was collected from a sample of 195 respondents from the managerial side of a virtual university in Pakistan using an online survey. Structural Equation Modelling was used to predict the relationships between identified factors and big data adoption. According to the results, relative advantage, complexity, compatibility, top management support, financial resources, human expertise and skills, competitive pressure, security and privacy, and government policies were significant determinants of big data adoption. However, results revealed an insignificant relationship between the information technology

infrastructure and big data adoption. The findings further revealed the significant moderating effects of university age on government policies, security and privacy concerns with big data adoption. Similarly, substantial moderating effects of the university size between information technology infrastructure and big data adoption were found. The findings from this study can assist the ministry of education, higher education institutions administrators, and big data service providers in the adoption of big data for the education sector. Future studies could be longitudinal, conducted at the post-adoption stage and at other educational levels.

Keywords: Big data adoption, Theoretical model, Higher education institution, Structural equation modelling, Technology Organization Environment, Diffusion of Innovation.

MODEL TEORI UNTUK PENGADAPTAISAN DATA RAYA DI INSTITUSI PENDIDIKAN TINGGI DI PAKISTAN

ABSTRAK

Pengadaptasian data raya telah mendapat perhatian luar biasa dari para eksekutif di pelbagai bidang. Namun, ia masih belum diterokai dengan baik di sektor pendidikan, di mana sejumlah besar data akademik dihasilkan. Institusi pengajian tinggi Pakistan menghadapi kesukaran untuk meningkatkan kecekapan pengurusan pendidikan yang diperlukan untuk memenuhi tuntutan masa depan. Oleh itu, terdapat keperluan pengadaptasian data raya di institusi pengajian tinggi Pakistan untuk meningkatkan keupayaan pengurusan. Walaubagaimanapun, terdapat kekurangan model teori dan faktor yang mempengaruhi pengadaptasian data raya di institusi-institusi pengajian tinggi. Kajian ini bertujuan untuk membangunkan model teori dan mengenal pasti faktor-faktor yang mempengaruhi pengadaptasian data raya di institusi pengajian tinggi. Sepuluh faktor dikenal pasti dari literatur dan model teori dibangunkan. Teknologi-Organisasi-Persekutaran dan Penyebaran Inovasi diadaptasi sebagai teori dasar kajian ini. Sementara itu, kesan penyederhanaan ukuran universiti dan usia universiti terhadap pengadaptasian data raya ditambahkan pada model yang dibangunkan. Sebuah universiti maya di Pakistan, diiktiraf oleh Suruhanjaya Pengajian Tinggi Pakistan sebagai salah satu institusi pengajian tinggi Pakistan telah dipilih. Data dikumpulkan daripada sampel 195 responden dari pihak pengurusan universiti maya di Pakistan menggunakan tinjauan dalam talian. Pemodelan Persamaan Struktural digunakan untuk meramalkan hubungan antara faktor yang dikenal pasti dan pengadaptasian data raya. Menurut hasilnya, kelebihan relatif, kerumitan, keserasian, sokongan pengurusan atasan, sumber kewangan, kepakaran dan keterampilan manusia, tekanan kompetitif, keamanan dan privasi, dan tekanan pemerintah merupakan penentu penting dalam penadaptasian data

raya. Namun, hasil menunjukkan hubungan yang tidak signifikan antara infrastruktur teknologi maklumat dan pengadaptasian data raya. Penemuan ini selanjutnya menunjukkan kesan penyederhanaan yang signifikan dari usia universiti antara dasar kerajaan, keselamatan dan privasi dengan pengadaptasian data yang raya. Begitu juga, kesan penyederhanaan yang raya dari ukuran universiti antara infrastruktur teknologi maklumat dan pengadaptasian data raya didapati. Kajian ini dapat membantu kementerian pendidikan, pentadbir institusi pendidikan tinggi, dan penyedia perkhidmatan data raya untuk adaptasi data raya di sektor pendidikan. Kajian masa depan boleh membujur, dijalankan pada peringkat selepas pengadaptasian dan pada peringkat pendidikan lain.

Kata Kunci: Pengadaptasian data raya, Model teori, Sektor pendidikan tinggi, pemodelan persamaan struktur, Persekutuan Organisasi Teknologi, Penyebaran Inovasi

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TABLE OF CONTENTS

ABSTRACT	iii
ABSTRAK	v
ACKNOWLEDGEMENTS	vii
LIST OF FIGURES	xiii
LIST OF TABLES	xiv
LIST OF ABBREVIATIONS	xvi
CHAPTER 1: INTRODUCTION	1
1.1 Introduction.....	1
1.2 Problem Statement.....	5
1.3 Research Questions.....	6
1.4 Research Objectives.....	7
1.5 Research Scope.....	8
1.6 Structure of the Thesis	9
CHAPTER 2: LITERATURE REVIEW.....	12
2.1 Introduction	12
2.2 Overview of Big Data.....	12
2.3 Big Data Adoption.....	14
2.4 Theoretical Models used for Technology Adoption	17
2.4.1 Technology-Organization-Environment.....	17
2.4.2 Diffusion of Innovation	19
2.4.3 Technology Acceptance Model	20
2.4.4 Institutional Theory	20

2.4.5 Technology Task Fit	21
2.4.6 Human, Organization and Technology -Fit Theory	21
2.5 Big Data Adoption State of the Art	22
2.5.1 Issue and Domain	22
2.5.2 Respondents and Data Collection	23
2.5.3 Measuring Instrument and Data Analysis Technique	23
2.5.4 Limitations	24
2.6 Big Data Adoption Models and Factors	32
2.7 Models and Factors used for Technology Adoption in Higher Educational Studies..	38
2.8 Higher Education of Pakistan	44
2.8.1 Emergence of Technology Adoption in Higher Education Institutions of Pakistan.....	44
2.8.2 Virtual University	45
2.8.3 Virtual University of Pakistan	45
2.9 Research Gaps in the Literature.....	46
2.10 Summary.....	47
CHAPTER 3: RESEARCH METHODOLOGY	48
3.1 Introduction.....	48
3.2 Research Paradigms.....	48
3.2.1 Positivist Paradigm	50
3.2.2 Interpretivist Paradigm	52
3.2.3 Critical Paradigm	55
3.2.4 Discussion on Selected Paradigm	57
3.3 Research Design	58

3.3.1 Systematic Literature Method.....	61
3.4 Sampling Technique and Participants	64
3.5 Sample Size and Data Collection	64
3.6 Questionnaire Development and Validation.....	66
3.6.1 Instrument Development	66
3.6.2 Measurement of Items	71
3.6.3 Content Validity.....	78
3.7 Data Analysis Methods	86
3.7.1 Descriptive Data.....	86
3.7.2 Partial Least Squares Structural Equation Modelling	86
3.7.3 Structural Model Analysis	88
3.8 Pilot Study.....	90
3.9 Summary	97
CHAPTER 4: MODEL AND HYPOTHESES DEVELOPMENT	98
4.1 Introduction.....	98
4.2 Identify Factors and Research Model Development	98
4.2.1 Independent Constructs and Moderators for Big Data Adoption Model	98
4.2.2 Technology Organization Environment and Diffusion of Innovation	99
4.2.3 Extracted Factors through Big Data Adoption Studies	100
4.2.4 Selected Factors for the Model.....	103
4.3 Hypotheses Development	110
4.3.1 Technology Context	111
4.3.2 Organizational Context	114
4.3.3 Environment Context	116
4.4 Summary.....	120

CHAPTER 5: DATA ANALYSIS AND FINDINGS.....	121
5.1 Introduction.....	121
5.2 Demographic Analysis.....	121
5.2.1 Participants Profile.....	121
5.3 Model Assessment.....	123
5.3.1 Measurement Model (Outer-Model) Assessment.....	123
5.3.2 Structural Model (Inner-Model) Assessment	131
5.4 Summary.....	136
CHAPTER 6: DISCUSSION.....	137
6.1 Technology Factors and Hypotheses	138
6.1.1 Relative Advantage	138
6.1.2 Complexity.....	139
6.1.3 Compatibility.....	140
6.1.4 IT Infrastructure	141
6.2 Organization Factors and Hypotheses	143
6.2.1 Top Management Support	143
6.2.2 Financial Resources.....	144
6.2.3 Human Expertise and Skills	145
6.3 Environmental Factors and Hypotheses	146
6.3.1 Competitive Pressure	147
6.3.2 Security and Privacy.....	148
6.3.3 Government Policies	149
6.4 R ² Value.....	150
6.5 Summary.....	151
CHAPTER 7: CONCLUSION	152

7.1 Introduction.....	152
7.2 Research Accomplishments.....	152
7.2.1 Research Objective 1: To investigate the state of the art of big data adoption.....	152
7.2.2 Research Objective 2: To identify the factors that influence big data adoption in the higher education sector.....	153
7.2.3 Research Objective 3: To develop a theoretical model for big data adoption in the higher education institution.....	154
7.2.4 Research Objective 4: To validate a theoretical model for big data adoption in the higher education institution of Pakistan.....	155
7.3 Guidelines for Big Data Adoption based on the Findings	157
7.4 Contribution of the Study	160
7.5 Research Significance.....	161
7.6 Limitations.....	162
7.7 Future work.....	163
7.8 Conclusion	163
REFERENCES.....	165
APPENDICES	185
LIST OF PUBLICATIONS	205

LIST OF FIGURES

Figure 2.1: The Relationship of TOE with Adoption Decision.....	19
Figure 2.2: The Relationship of DOI with Innovational Adoption Decision	20
Figure 3.1: Research Steps	60
Figure 3.2: Articles Selection Process	63
Figure 3.3: Questionnaire Design Process	67
Figure 3.4: Format of Statement Criteria.....	70
Figure 4.1: Factors for Big Data Adoption Model	102
Figure 4.2: Proposed Theoretical Model for Big Data Adoption	119
Figure 5.1: Theoretical Model for Big Data Adoption (with hypothesis)	134
Figure 5.2: Theoretical Model for Big Data Adoption	135
Figure 7.1: Guidelines for the Big Data Adoption based on Finding.....	157

LIST OF TABLES

Table 1.1: Structure of the Thesis.....	11
Table 2.1: Big Data Adoption Studies.....	25
Table 2.2: Big Data Adoption Models and Factors	34
Table 2.3: Adoption in Higher Educational Studies.....	40
Table 2.4: Models and Factors used Adoption in Higher Educational Studies	42
Table 3.1: Relative Advantage Items.....	72
Table 3.2: Complexity Items	73
Table 3.3: Compatibility Items	73
Table 3.4: IT infrastructure Items.....	74
Table 3.5: Top Management Support Items	74
Table 3.6: Financial Resource Items	75
Table 3.7: Human Expertise and Skills Items	75
Table 3.8: Competitive Pressure Items	76
Table 3.9: Security and Privacy Concerns Items.....	76
Table 3.10: Government Policies Items.....	77
Table 3.11: University Age Items.....	77
Table 3.12: University Size Items	77
Table 3.13: Big data adoption Items.....	78
Table 3.14: Expert Profile.....	79
Table 3.15: Rating Scale for Expert Opinion	81
Table 3.16: Expert's Opinion in Terms of Simplicity of Items	82
Table 3.17: Experts Opinion in Terms of Relevancy of Items	84
Table 3.18: Results of Questionnaire (Pilot Study).....	92

Table 3.19: Pilot Study Results of Cross Loading.....	95
Table 3.20: Pilot Study Results Fornell-Larcker Criterion.....	97
Table 4.1: Extracted Constructs through Big Data Adoption Studies	101
Table 5.1: Descriptive Analysis (Respondents' Profiles).....	123
Table 5.2: Results of the Factor Loading, Reliability, and Convergent Validity	124
Table 5.3: Fornell-Larcker Criterion	127
Table 5.4: Heterotrait-Monotrait Ratio (HTMT).....	128
Table 5.5: Cross Loading.....	129
Table 5.6: Results of Hypotheses (Direct Relationships)	132
Table 5.7: Results of Hypotheses (Moderating Relationships)	133
Table 6.1: Relative Advantage Results.....	139
Table 6.2: Complexity Results	140
Table 6.3: Compatibility Results	141
Table 6.4: IT Infrastructure Results.....	143
Table 6.5: Top Management Results	144
Table 6.6: Financial Resources Results	145
Table 6.7: Human Expertise and Skills Results.....	146
Table 6.8: Competitive Pressure Results	148
Table 6.9: Security & Privacy Results.....	149
Table 6.10: Government Policies Results.....	150

LIST OF ABBREVIATIONS

Abbreviations	Description
BDA	Big Data Adoption
TOE	Technology Organization Environment
DOI	Diffusion of Innovation
SEM	Structural Equation Modelling
ICT	Information and Communications Technology
HEC	Higher Education Commission
PLS	Partial Least Squares
VU	Virtual University

CHAPTER 1: INTRODUCTION

1.1 Introduction

The term "big data" refers to a huge volume of data (Chamikara, Bertok, Liu, Camtepe, & Khalil, 2019; Rani & Kant, 2020; Monino, 2021). Due to the advent of computers, the internet, and mobile technology, a large amount of data is produced daily (Abdel-Basset, Mohammed, Smarandache, & Chang, 2018; Shorfuzzaman, Hossain, Nazir, Muhammad, & Alamri, 2019; Xiao & Xie, 2021). Therefore, the size of data is increasing day by day and recently reached several xenabytes (Nazarenko & Khronusova, 2017).

The big data is in the forms of structured (in the form of tables), unstructured (videos, audio, images, comment, follower, likes, and chats.), and semi-structured data (text data) (Liu, Sun, Higgs, Zhang, & Huang, 2017; Rahman & Reza, 2021). Big data services provide advanced procedures to analyze different kinds of data, predict the results, and produce a fast-accurate response in a short time (Lee, 2018; Camargo, Seles, Jabbour, Mariano, & Sousa, 2018; Walter et al., 2021).

Big data adoption helps in enhancing the sub-structure of the institution. It can be helpful to analyze huge amounts of information instantly and get various benefits (Al-Qirim, Tarhini, & Rouibah, 2017; Ang, Ge, & Seng, 2020; Sun et al., 2020). Big data adoption can be helpful in various ways. For example:

- Provide flexible infrastructure (Arfat, Usman, Mehmood, & Katib, 2020).
- Extract relevant information easily (Zhao, McGrath, Huang, & Wu, 2018).

- Enhance staff competency, performance, and capabilities (Mandal, 2018; Painuly, Sharma & Matta, 2021).
- Provide cost-effective solutions (Arfat, Usman, Mehmood, & Katib, 2020).
- Promote decision-making culture (Thirathon, Wieder, Matolcsy, & Ossimitz, 2017; Rani & Kant, 2020).
- Manage critical situations and tackle opponent pressure (Müller, Fay, & Brocke, 2018; Park & Kim, 2021).

Currently, a large amount of academic data is produced through online learning and teaching activities (Chaurasia & Frieda, 2017; Dinter, Jaekel, Kollwitz, & Wache, 2017; Manasa, Seetha, & Viswanadha, 2021). However, the academic sector is dealing with challenges such as:

- The absence of required tools (Daud, Wan-Hanafi, & Hanapiyah, 2018; Pn & Baglodi, 2018; Fischer et al., 2020).
- Data gathering, storage and processing issues (Ben-Porath & Ben-Shahar, 2017; Daud, Wan-Hanafi, & Hanapiyah, 2018; Chen, Li, Lin, & Wang, 2021).
- Lack of infrastructure (Mukhtar & Sultan, 2017).
- Insufficient management support (Daud et al., 2018; Mukhtar & Sultan, 2017; Vatsala et al., 2017; Fischer et al., 2020).
- The inadequacy of expertise and proper training for big data adoption (Deepa & Blessie, 2017; Mukhtar & Sultan, 2017; Daud et al., 2018; Baig et al., 2020).
- Scarcity of financial resources (Vatsala & Jadhav, 2017; Chweya, Ajibade, Buba, & Samuel, 2020).
- Privacy issues (Reidenberg & Schaub, 2018; Chen, Li, Lin, & Wang, 2021).

- Security and consent (Ben-Porath & Ben-Shahar, 2017; Daud et al., 2018; Bai et al., 2021).
- Ethical considerations (Mukhtar & Sultan, 2017; Pn & Baglodi, 2018; Chweya, Ajibade, Buba, & Samuel, 2020).

Big data adoption is significantly increasing in different fields of endeavour such as insurance and construction (Dresner Advisory Services, 2017), healthcare (Wang, Kung, & Byrd, 2018; Chen, Lin, & Wu, 2020), telecommunication (Ahmed et al., 2018), tourism (Yadegaridehkordi, Nilashi, Nasir, & Ibrahim, 2018), banking and finance (Almoqren & Altayar, 2016) and e-commerce (electronic commerce) (Wu & Lin, 2018, Chandra & Kumar, 2018; Supriyanto, Bakti, Furqon, 2021). According to Dresner Advisory Services (2017), technology (14%), financial services (10%), consulting (9%), healthcare (9%), education (8%), and telecommunication (7%) are the most active sectors in producing a vast amount of data. With the advent of big data, now higher education institutions can access students' academic performance and learning patterns (Oi, Yamada, Okubo, Shimada, & Ogata, 2017; Black & William, 2018; Dahdouh, Dakkak, Oughdir, & Messaoudi, 2018; Zheng, & Bender, 2019; Supriyanto, Bakti, & Furqon, 2021). Academic data can help teachers to analyze their teaching pedagogy and affect changes according to students' needs, and individual student preferences have been introduced (Holland, 2019; Seufert, Meier, Soellner, & Rietsche, 2019). The improvement in the educational sector depends upon acquisition and technology. Large-scale administrative data can play a tremendous role in managing various academic problems (Sorensen, 2018). Therefore, it is essential to employ the effectiveness of big data in the education sector.

A theoretical model is a pre-existing, acceptable theory in scholarly literature. Technology–Organization–Environment (TOE) (Tornatzky et al., 1990), Technology Acceptance Model (TAM) (Davis, 1989), Diffusion of Innovations (DOI) (Rogers, 1995), and Task-Technology Fit (TTF) (Goodhue & Thompson, 1995) are commonly used Information Systems (IS) adoption theories for explaining the adoption decisions of IT at an individual or organizational level. These theories assist in analyzing the factors that affect technology adoption decisions.

The need and importance of technology adoption have also been accepted by the higher education sector (Baig, Shuib, & Yadegaridehkordi, 2021). However, research related to new technology adoption is limited in developing countries, especially in Pakistan (Afridi & Chaudhry, 2019). The current global economic platform is built on technological infrastructure. In Pakistan, technology adoption can improve education and economic growth. However, in technology adoption, there are some issues like a lack of needed skill sets and tools (Rahman & Reza, 2021). Moreover, there is a lack of technology adoption models (Cabrera-Sánchez & Villarejo-Ramos, 2020). As the digital revolution continues, organizations are looking for an adoption model to adopt emerging technology quickly (Bai et al., 2021). The adoption model can be helpful in managing the adoption process smoothly (Chweya, Ajibade, Buba & Samuel, 2020).

Based on a literature review, 559 research articles related to big data in education were studied over the last six years (Baig, Shuib, & Yadegaridehkordi, 2020). This study found that the education sector is still in the early stage of big data adoption. Another review of research analyzed the big data adoption models through the articles published in the last four years (Baig, Shuib, & Yadegaridehkordi, 2019). According to this study, the theoretical model for big data adoption and the factors that influence big data adoption in the education sector are still unexplored.

The adoption of big data can be smooth if the factors affecting adoption are identified and appropriately addressed by using a theoretical model (Weerasinghe, Pauleen, Scahill, & Taskin, 2018; Surbakti, Wang, Indulska, & Sadiq, 2019). Therefore, this study aims to identify the factors that affect big data adoption in the higher education sector and to develop a theoretical model for big data adoption for higher education institutions.

1.2 Problem Statement

Big data adoption studies have been conducted on firms (Yadegaridehkordi et al., 2020), organizations (Mikalef et al., 2020), and companies (Cabrera-Sánchez & Villarejo-Ramos, 2020). However, big data adoption is still not well explored in higher education institutions, where a huge quantity of data is produced through various activities (Baig et al., 2020).

In the higher education sector, data is expanding gradually as the number of students is growing (Nazarenko & Khronusova, 2017). Students and faculty staff play the role of end-users who use the provided Information and Communications Technology (ICT) facilities (Sabi, Uzoka, Langmia, Njeh, & Tsuma, 2017). In contrast, database administrators, network administrators, and Information Technology (IT) managers directly handle all data issues and facilitate ICT services in universities (Alajmi et al., 2018). Adoption decisions are taken at various levels of the university administration.

The higher education institutions of developing countries are facing difficulties in upgrading the educational, and managerial competency that is needed to fulfil future demands (Alalawneh & Alkhatib, 2021). Big data adoption is necessary for the higher education sector as it provides various competitive advantages that help to cater the future needs and upgrade managerial proficiency (Alhazmi, 2021). Big data adoption

can be amplified by proposing a theoretical framework (Weerasinghe, Pauleen, Scahill & Taskin, 2018).

Nevertheless, the previous studies mainly highlighted the benefits of adoption in the educational realm (McLeod, Bliemel, & Jones, 2017). But the issue here is a lack of a theoretical model to explore the factors that affect big data adoption in higher education institutions, mainly in developing countries (Umezuruik & Ngugi, 2020; Alalawneh & Alkhatib, 2021). The big data adoption theoretical model is needed to predict the situation and phenomena and pave the path for smooth big data adoption in higher education institutions.

Meanwhile, moderating variables can be helpful predicting the relations in the proposed theoretical model; the examination of moderating effects in big data adoption studies has been overlooked in the literature (Yadegaridehkordi et al., 2020). Age and size are important moderating factors that have been examined in many contexts (Ashegh-Oskooeea & Mazloomi, 2018; Salah, Yusof & Mohamed, 2021; Alshirah, Lutfi, Alshirah, Saad, Ibrahim, & Mohammed, 2021).

However, the moderating roles of these significant factors on big data adoption have not been explored in the literature (Yadegaridehkordi et al., 2020). University age and university size are used as moderators to analyze the effects that may strengthen the relationships between the predictors and big data adoption. Therefore, this study addresses such gaps by identifying the factors that affect big data adoption in the higher education sector and developing and validating a big data adoption theoretical model for a higher education institution.

1.3 Research Questions

The research questions are as follows:

RQ1: What is the state of the art of big data adoption?

RQ2: What are the factors that influence big data adoption in higher education sector?

RQ3: How to develop a theoretical model for big data adoption in the higher education institution?

RQ4: How to validate a theoretical model for big data adoption in the higher education institution of Pakistan?

1.4 Research Objectives

The primary aim of this study is to identify the factors that affect big data adoption in higher education and propose a big data adoption theoretical model for the higher education sector. Therefore, the primary objectives of this research are as follows:

RO1: To investigate the state of the art of big data adoption.

RO2: To identify the factors that influence big data adoption in the higher education sector.

RO3: To develop a theoretical model for big data adoption in the higher education institution.

RO4: To validate a theoretical model for big data adoption in the higher education institution of Pakistan.

1.5 Research Scope

This research aims to develop a theoretical model for big data adoption in the higher education sector. In higher education institutions, the primary role of database

administrators, network administrators, and campus managers is to provide secure, consistent and reliable services such as databases and storage to solve multifaceted data problems, website issues, system administration, networking and infrastructure. This study targeted database administrators, network administrators, IT administrators and campus administrators as they are the primary decision-makers for big data adoption. Therefore, the unit of analysis is organizational.

The data collection process is conducted within the higher education institution named Virtual University (VU) of Pakistan. The VU of Pakistan is the first university-based on modern ICT entirely. It was established by the Government as a public sector, not for profit institution, with a clear mission: to provide extremely affordable world-class education to aspiring students (Malik, 2020). It holds a Federal Charter, making its degrees recognized and accepted all over the country as well as overseas. It has 200 campuses located in over 100 cities and more than 100,000 students. In Pakistan, no other university has such a large number of campuses and managerial staff.

The VU has been awarded the highest rank by the Quality Assurance Agency (QAA) of the Higher Education Commission twice in a row in its annual assessment. Therefore, any high-ranked university is expected to present the best performance in key areas such as adopting the latest technology. It can be a benchmark for improvement which means other universities can set targets and manage processes according to high-ranked institutions.

1.6 Structure of the Thesis

This research comprises seven chapters. The structure of the thesis is presented in Table 1.1. The first chapter provides an introduction to big data and highlights the issues related to managing the big data adoption process in the education sector. The

introduction is based on basic big data concepts and types of big data. The introduction contains the importance of big data adoption. Additionally, related literature was also reviewed. This chapter also discusses the research problem that big data adoption needs to explore in the higher education domain. Although the concept of big data has existed for more than a decade, there is still a need for factors and theoretical models for big data adoption in the higher education sector. Moreover, this chapter describes the objectives and research questions of the study. Furthermore, the scope of the study is discussed.

The second chapter presents the literature review. It describes an overview of big data and big data adoption and its benefits. Moreover, it provides an outline of the theoretical models used for technology adoption. Furthermore, it describes the big data adoption state of the art. This chapter illustrates big data adoption models and factors. Models and factors used for technology adoption in higher education studies. It also gives an overview of higher education in Pakistan. Moreover, it illustrates the research gap.

The third chapter presents the research methodology. Research paradigms and research design are discussed. The sampling technique, participants, sample size, and data collection procedures are also discussed in this chapter. This chapter highlights the instrument development and data analysis tools and methods involved.

The fourth chapter covers the research model and hypotheses' development. It describes the hypotheses development and a diagrammatic view of the proposed model. The fifth chapter presents data analysis and findings. It covers model analysis and testing of hypotheses. The sixth chapter presents the discussion of the findings.

The final chapter presents the conclusion of this study. It discusses the research accomplishments and presents guidelines that have been developed based on the findings.

The contributions and significance of this study, its limitations, and future research directions are also provided in this chapter.

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Table 1.1: Structure of the Thesis

Chapter	Description
1- Introduction	Overview Problem Statement Research Questions Research Objectives Research Scope
2- Literature Review	Overview of Big Data Big Data Adoption Theoretical Models used for Technology Adoption Big Data Adoption State of the Art Big Data Adoption Models and Factors Models and Factors used for Technology Adoption in Higher Educational Studies Higher Education of Pakistan Research Gaps in the Literature
3- Research Methodology	Research Paradigms Research Design Sampling Technique Sample Size and Data collection Questionnaire Development and Validation Data Analysis Methods Pilot Study
4- Model and Hypotheses Development	Factors and Research Model Development Hypotheses Development
5- Data Analysis and Findings	Model Assessment
6- Discussion	Discussion on Findings
7- Conclusion	Research Accomplishments Guidelines for Big Data Adoption based on the Findings Contribution of the Study Research Significance Limitations Future work

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter presents the literature review related to the research realm. This starts with an overview of big data. It is followed by big data adoption. It also explores the big data adoption benefits. Additionally, it provides details of theoretical models used for technology adoption. Moreover, it describes the big data adoption state of the art. This chapter also covers big data adoption models and factors. Furthermore, it illustrates the models and factors used by other studies. It is followed by a discussion of the big data adoption factors. Moreover, it discusses the models and factors used for adoption in higher education studies. It also discusses higher education in Pakistan. Furthermore, it illustrates the research gaps.

2.2 Overview of Big Data

Big data is defined as a large dataset that cannot be controlled or examined through conventional databases (Mishra, Luo, Jiang, Papadopoulos, & Dubey, 2017; Lin, Wang, Li, & Gao, 2019; Ghasemaghaei & Calic, 2020; Supriyanto, Bakti, Furqon, 2021). From a banking and finance perspective, it is “regularly expanding” information that is difficult to process through traditional data storage (Pérez-Martín, Pérez-Torregrosa, & Vaca, 2018; Rani & Kant, 2020).

In contrast, some scholars consider big data as a business approach that helps organizations to analyze a large amount of information (Wright, Robin, Stone, & Aravopoulou, 2019; Park & Kim, 2021). Moreover, few scholars described big data as a large and complex computerized dataset (Safhi, Frikh, & Ouhbi, 2019). There is no

fixed standard measurement on “what size should be considered large data sets” (Lee, 2017; Xiao & Xie, 2021).

Thus, there is no universal definition for distinguishing big data from all perspectives (Mikalef et al., 2020). However, the term "big data" has expanded significantly over the past few years (Arfat et al., 2020). It gained popularity in the early 2000s with the arrival of electronic shopping (Oussous, Benjelloun, Lahcen, & Belfkhir, 2018).

Big data is generated from multiple resources such as websites, graphical data, banks, and social media (Chaurasia & Frieda, 2017; Painuly, Sharma, & Matta, 2021). This data can be in the form of structured, unstructured, or semi-structured. The speed at which data is delivered is the most critical factor in big data adoption.

Big data is further characterized by three (3) V's, Volume (amount of data), Velocity (speed to access data), and Veracity (types of data) (Lee, 2017). Zhang, Ren, Liu, Xu, Guo, & Liu (2017) classified big data into five (5); Volume, Velocity, Variety, Veracity, and Value. However, Saggi, & Jain (2018) characterized big data into 7V's: Volume, Velocity, Variety, Valence, Veracity, Variability, and Value. Moreover, Volume possessed data storage challenges; Variety is related to data heterogeneity, Velocity acquires data processing provocations, Veracity is procured to the accuracy of data, Valence is associated with complexity, Value is linked to revenue and Variability is allied to data inconsistency confronts.

Big data has a massive number of advantages for the worldwide economic system (Johnson, Gray, & Sarker, 2019; Painuly, Sharma, & Matta, 2021). Its advantages attract different representatives and bring rivalry among enterprises. Now, it is one of the most significant information technology trends. Companies prefer employees that are armed with big data related skills and abilities (Park & Kim, 2021). Pastorino et al.

(2019) summed up that big data is beneficial for US health care and public organizations. Due to the advancement in technologies, it is now not only useful as big data but also helpful in solving miscellaneous problems related to banks, education, and the health sector (Fatt & Ramadas, 2018; Wang, Yang, Wang, Sherratt, & Zhang, 2020). Earlier, banks generated a large amount of data through ordinary dealings with customers, which has been discarded in the form of books. Due to the advent of technology, the same data is used for customer satisfaction, bank advancement, and better decision-making (Tabesh, Mousavidin, & Hasani, 2019; Chen, Li, Lin, & Wang, 2021).

2.3 Big Data Adoption

Big data adoption is defined as a ‘process and intention through which institutions find innovative ways to enhance productivity, predict risk, and satisfy customers more effectively and efficiently’ (Al-Qirim, Tarhini, & Rouibah, 2017). "Adoption" is a phase in which institutions choose technology for their use (Nadal, Doherty, & Sas, 2019). The adoption of big data might be laborious and have a big budget, but the return advantages may develop the path to success in the long run (Al-Qirim, Tarhini, & Rouibah, 2017; Chen, Lin, & Wu, 2020). Big data is generated by almost every field. Therefore, adoption should be expected from all fields.

Many sectors have already adopted big data (Tabesh, Mousavidin, & Hasani, 2019). Other areas like education and health care are still in the initial stages of adoption (Murumba & Micheni, 2017; Fatt & Ramadas, 2018; Chen, Lin & Wu, 2020). The adoption of big data can be enhanced in other fields if factors affecting adoption are analyzed and appropriately addressed by using the proper theoretical framework (Weerasinghe, Pauleen, Scahill, & Taskin, 2018; Cabrera-Sánchez & Villarejo-Ramos, 2020). Big data adoption can considerably improve the managerial side of the

educational sector (Khan, Shakil, & Alam, 2017). Consequently, adoption will directly enhance the overall performance of institutions.

- **Benefits of Big Data Adoption**

The benefits of big data adoption from a managerial perspective is categorized and discussed as below:

- a. Cost Saving*

Big data adoption has enormous potential to cut off the cost and provide instant digital-based solutions. Most organizations are now producing large amounts of data (Bai et al., 2021). This data can be helpful for organizations to gain various competitive advantages and make profitable decisions. Big data adoption is beneficial for extracting information useful to grow a business (Mikalef et al., 2020). Through adoption, constructive and unconstructive data can be easily differentiated. Extant studies examine that 68% of organizational executives invest in big data adoption while 32% plan to invest in the near future (Oussous et al., 2018; Pastorino et al., 2019). Big data is highly valuable for organizations to get maximum benefits in terms of cost reduction. It enables the development of successful strategies and plans that promote agile working environments and provide opportunities to reduce overall organizational work costs (Raguseo, 2018).

- b. Performance and Scalability*

Big data adoption plays a significant role in enhancing the performance and scalability of organizations and banks. Data is growing at a rate of 40 to 50 percent per year (Abraham, Jarmin, Moyer, & Shapiro, 2019). So, it is challenging to manage a large amount of data with existing stored procedures and get instant responses. Big data

adoption manages a large scale of data and provides fast retrieval techniques that are helpful to give instant query responses and augment the overall performance of an organization (Siddiqa, Karim, & Chang, 2017).

c. Increase Staff Competency and Promote Decision Taking Culture

Big data adoption promotes data-driven decision-based culture, which helps heighten employee competency (Nisar, Nasir, Jamshed, Naz, Ali, & Ali, 2020). After adoption, the organization staff becomes pro-active while taking decisions instead of unreactive action. Big data adoption is beneficial making better decisions for organizations (Thirathon, Wieder, Matolcsy, & Ossimitz, 2017; Park & Kim, 2021). It sequentially amplifies the competency of employees; encourages decision-based culture, which enhances the productivity and efficiency of the entire organization (Günther, Rezazade, Huysman, & Feldberg, 2017).

d. Improve the Infrastructure

Big data adoption generates various benefits and improves the overall IT infrastructure of organizations (Arfat et al., 2020). Organizations increase the storage capacity to meet competency and performance requirements. It allows dynamic provision for parallel processing and hires ICT-trained academic staff to support and manage varied data types. To maintain an uncongested network environment for adoptions, organizations developed new network links with servers and increased switch ports, bandwidth, and internet connections (Camargo, Seles, Jabbour, Mariano, & Jabbour, 2018). The implementation of all innovative facilities accelerates the overall system and improves the managerial infrastructure.

e. Manage Competitive Pressure

Competitive pressure affects organizations' inducement to produce or invent some innovative item. Big data adoption supports competitive pressure by creating discriminated price strategies and observing consequences instantly (Park & Kim, 2021). For instance, through big data adoption, actual revenue benefits can be analyzed, or the price can be analyzed to compete with other products (Müller, Fay, & Brocke, 2018; Caesarius & Hohenthal, 2018).

f. Market Scope and Client's Loyalty

Clients like to visit need-driven markets or places. By adopting big data, organizations can leverage the client's needs and future prospects accordingly (Park & Kim, 2021). According to their purchase record, clients can be categorized into distinct tiers (Raguseo, 2018). Thus, it will be a great chance to develop long-term relationships with customers by fulfilling their needs.

g. Hiring Organizational Staff

Big data adoption provides HR executives with a variety of tools for identifying employees by accessing appropriate profile data from various job websites (Baig, Shuib, & Yadegaridehkordi, 2019). This is extremely helpful for organizations to complete the staff hiring process quickly and reliably (Prasad, Zakaria, & Altay, 2018). It can be concluded from the above discussion that big data adoption, scope, and future challenges can be observed and recognized at an early stage (Pastorino et al., 2019).

2.4 Theoretical Models used for Technology Adoption

This section of the study discusses the theoretical models used for technology adoption.

2.4.1 Technology-Organization-Environment

Tornatzky and Fleischer proposed the Technology-Organization-Environment (TOE) framework in 1990. It influenced the decision to adopt technology in three ways: technology, organization, and environmental context. The TOE framework is a multidisciplinary framework, as shown in Figure 2.1. Previous studies have analyzed its wide pertinence, versatility, and affinity in different contexts, including education (Nugroho, 2017), learning management systems (Nyeko & Ogenmungu, 2017), e-commerce, and e-business (Aljowaidi, 2015).

TOE has effectively explained technological adoption. In addition, the TOE framework allows in-depth analyses of what elements should be considered that affect big data adoption (Verma & Bhattacharyya, 2017). The technological context comprises internal and external technologies and all required tools, software, processes, etc. It highlights how technological attributes influence the adoption process. The organizational context reveals the firm environment, resources and characteristics that help in the adoption or rejection of technological innovations. It reflects how organizational attributes facilitate or influence technological innovations. The environmental context shows the external environment and culture of an organization in which firms carry on their business. However, prior studies found that the environment includes the structure of the organizations, opponent pressure, and regulatory concerns. Organization external pressure and a non-supportive attitude directly impact the organization's environment and employee progress (Tornatzky et al., 1990).

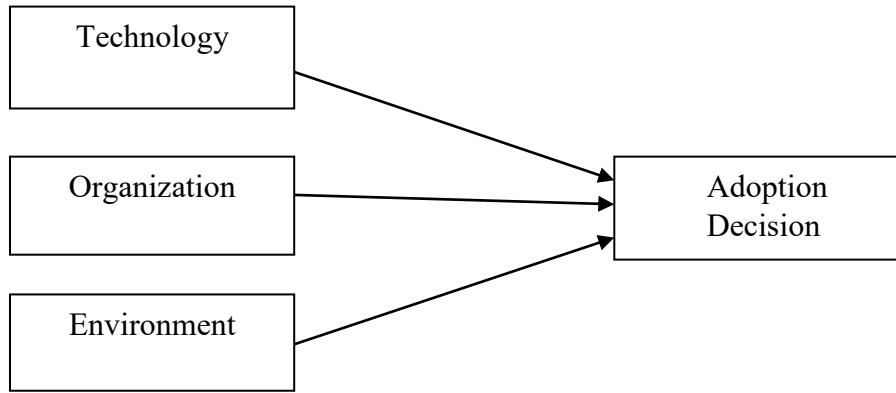


Figure 2.1: The Relationship of TOE with Adoption Decision (Tornatzky and Fleischner, 1990)

2.4.2 Diffusion of Innovation

Diffusion of Innovation (DOI) describes the innovation diffusion process. Innovation is like a novelty that takes time in the adoption or rejection by an organization, entire community, groups or individual. Adoption decision is optional at the individual level. Adoption or rejection does not only rely on all groups of members. Innovation acceptance can be seen through the individual rather than the whole community. However, when adoption is for the whole organization, the decision is taken from the entire organization or a group of members, known as a collective decision. Authority decisions can adopt or reject the innovation that is accepted by a small number of technical experts. To understand the diffusion of innovation, a comprehensive understanding of organizations' adoption behaviour is necessary (Rogers, 1995). According to DOI, adoption-decision can be affected by five factors: Relative advantage, complexity, compatibility, trialability, and observation (Figure 2.2).

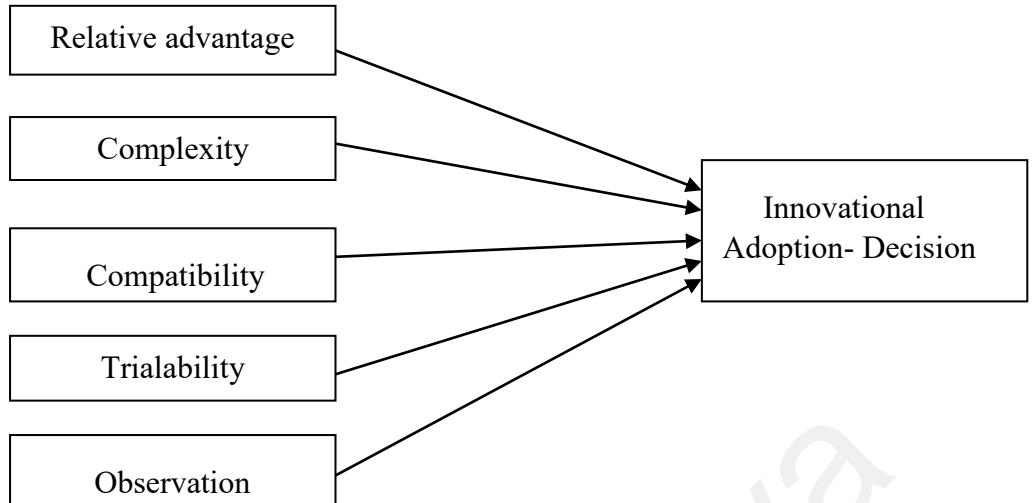


Figure 2.2: The Relationship of DOI with Innovational Adoption Decision
(Rogers, 1995)

2.4.3 Technology Acceptance Model

The Technology Acceptance Model (TAM) was originally developed to predict the acceptance or adoption of innovations (Davis, 1989). TAM has two aspects: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is an independent construct. It is when an individual starts considering that employing a specific system would increase their job performance. PEOU is defined as "the level at which someone should start to believe that a specific system has become effortless". Individual attitude toward use; determine the intention to use sequentially. TAM is highly qualified for post-adoption stage. It is mostly recommended to collect data from end-users. This theory aimed to enlighten the impact of user intention.

2.4.4 Institutional Theory

Institutional Theory (IS) represents the institutional environments that are important in determining the organizational formation and further activities (Voronov & Weber, 2020). According to this theory, organizational adoption decisions are influenced by organizational objectives and external environmental, cultural, and social factors. The

theory highlighted that organizational decisions are affected by similar types of pressures that come from the other side (David, Tolbert, & Boghossian, 2019). The firm's decision to adopt big data is not internally driven, but the pressure comes from the opponent, customers, trade associates, market and government. Due to this pressure, organizations are under pressure to reproduce the actions of leaders, and industries have become homologous over time. Organizations can adopt new innovations for trading opponents to maintain their interior stability. In a favourable environment, the government can support organizations to adopt big data by providing proper facilities and relaxation in official laws. Organizations will be under less pressure if the government encourages a firm to adopt big data (Voronov & Weber, 2020).

2.4.5 Technology Task Fit

Technology Task Fit (TTF) is another theoretical model for examining the relationships between information systems and individual performance. The TTF model focuses on innovation utilization and the value it creates. In a setting where innovation is utilized by individuals to perform specific tasks or sets of undertakings, the model's reason is that innovation is made. Therefore, TTF is significantly influenced by both task and technology characteristics; and, in turn, directly related to the users' performance and utilization (Goodhue & Thompson, 1995).

2.4.6 Human, Organization and Technology -Fit Theory

The Human, Organization, and Technology (HOT) fit theory was introduced by DeLone and McLean in 1992. It is mostly used to assess the quality of the information system. It is easy to apply in various evaluation contexts. Human, Organization and Technology (HOT) fit theory has been used for different quality checking systems.

2.5 Big Data Adoption State of the Art

A comprehensive literature review was conducted in order to identify big data adoption and its associated theoretical models, factors, and challenges. The complete discussion of the Systematic Literature Review (SLR) method is presented in Chapter 3. The comprehensive research helped to identify the state of the art of theoretical models used by various studies for big data adoption.

2.5.1 Issue and Domain

It has been found that previous studies analyzed the factors that affect big data adoption in firms (Park, Kim, & Paik, 2015; Verma and Bhattacharyya, 2017; Yadegaridehkordi et al., 2020) and developed a big data adoption model for firms (Kang & Kim, 2015). Moreover, extant studies analyzed the factors that affect big data adoption in companies and proposed big data adoption model for companies (Yin, 2015; Chen, Kazman, & Matthes, 2015; Soon, Lee & Boursier, 2016; Yadegaridehkordi, Hourmand, Nilashi, Shuib, Ahani, & Ibrahim, 2018).

Furthermore, Salleh & Janczewski (2016), Potter (2016), Gunasekaran et al. (2017), Nguyen & Petersen (2017), Lai, Sun, & Ren (2018) and Sun, Cegielski, Jia, & Hall (2018) identified the factors that affect big data adoption in organizations. However, Mneney & Belle (2016) study showed the readiness of big data adoption in the organization domain. Another study conducted by Verma, Bhattacharyya, & Kumar (2018) proposed and validated a big data adoption model for the business domain. It has been found that in the education domain, McLeod, Bliemel, & Jones (2017) analyzed the changes in big data adoption and analytics, and Matsebula & Mnkanla (2016) highlighted the IS and innovation adoption. Moreover, Wu, Li, Liu, & Zheng (2017) investigated the impact of big data and analytics on the health IT market. The

extant literature showed that the factors affecting big data adoption had been analyzed in banks (Almoqren & Altayar, 2016) and supermarkets (Ochieng, 2015).

2.5.2 Respondents and Data Collection

Most of the big data adoption studies used surveys for data collection (Kang & Kim, 2015; Almoqren & Altayar, 2016; Soon, Lee, & Boursier, 2016; Nguyen & Petersen, 2017; Wu, Li, Liu, & Zheng, 2017; Verma, Bhattacharyya, & Kumar, 2018; Yadegaridehkordi et al. 2020). The respondents of big data adoption studies were top managers and executive level employees (Nguyen & Petersen, 2017; Yadegaridehkordi et al. 2020), senior managers (Yadegaridehkordi, Hourmand, Nilashi, Shuib, Ahani, & Ibrahim, 2018), IT managers (Lai, Sun, & Ren, 2018), big data users (Verma, Bhattacharyya, & Kumar, 2018) and experts (Park, Kim, & Paik, 2015).

However, few studies used face-to-face semi-structured interviews (Yin, 2015; Potter, 2016; Verma & Bhattacharyya, 2017). The interviews were conducted with enterprises and service providers (Verma & Bhattacharyya, 2017), senior managers (Potter, 2016), retailers, vendors, and IT service providers (Mneney & Van Belle, 2016).

2.5.3 Measuring Instrument and Data Analysis Technique

Most of the big data adoption studies were quantitative and used five-point or seven-point Likert scales (Soon, Lee, & Boursier, 2016; Salleh & Janczewski, 2016; Verma, Bhattacharyya, & Kumar, 2018; Yadegaridehkordi et al., 2020). However, few studies employed qualitative methods (Potter, 2016; Mneney & Van Belle, 2016; Verma & Bhattacharyya, 2017).

2.5.4 Limitations

It has been found that most big data adoption studies use a small sample size (Almoqren & Altayar, 2016; Salleh & Janczewski, 2016; Verma, Bhattacharyya, & Kumar, 2018) and lack an empirical foundation (McLeod, Bliemel, & Jones, 2017). Extant big data adoption studies were limited to firms (Yadegaridehkordi et al., 2020), organizations (Lai, Sun, & Ren, 2018; Sun, Cegielski, Jia, & Hall, 2018), companies (Soon, Lee, & Boursier, 2016; Gunasekaran et al. 2017) and the market (Wu, Li, Liu, & Zheng, 2017). Education is a less-explored domain. Previous educational studies have highlighted the need and importance of big data adoption (Matsebula & Mnkanla, 2016; McLeod, Bliemel, & Jones, 2017). Moreover, moderators are not well explored in previous big data adoption studies (McLeod, Bliemel, & Jones, 2017; Yadegaridehkordi et al., 2020). Furthermore, there is still a lack of studies in the educational domain that explores big data adoption by proposing a theoretical model and examining factors.

The summary of reviewed studies of big data adoption is presented in Table 2.1.

Table 2.1: Big Data Adoption Studies

Study	Issue	Domain	Respondents	Data Collection	Measuring Instrument	Data Analysis Technique	Limitation
Yadegaridehkordi et al. (2020)	Identified Influence of big data adoption on manufacturing companies	Firms	418 top managers and/or owners of Malaysian SMEs	Survey	Five-point Likert scale	Quantitative	Limited to companies
Yadegaridehkordi et al. (2018)	Analyzed Impact of big data adoption on Firm Performance in Hotel Industry	Companies	234 senior managers of manufacturing companies of Malaysia	Survey	-	Quantitative	Limited to companies
Sun, Cegielski, Jia, & Hall (2018)	Identified the main factors that affect big data adoption at the organizational level	Organization	Content analysis	Set the criteria for including excluding and developing coding protocol	-	Content analysis was collected from previous qualitative studies	Lack empirical research

Table 2.1: Big Data Adoption Studies (Con't)

Study	Issue	Domain	Respondents	Data Collection	Measuring Instrument	Data Analysis Technique	Limitation
Lai, Sun, & Ren (2018)	Identified the determinants of big data adoption in logistics and supply chain management	Organization	210 from IT managers at China	Survey	Seven-point Likert-type scale	Quantitative	Respondent's viewpoint may not fully represent the organization
Verma, Bhattacharyya, & Kumar (2018)	Proposed and validate a model	Business	150 BD users from India	Survey	Five-point Likert scale	Quantitative	Small sample size
McLeod, Bliemel, & Jones (2017)	Explored the changes in BDA and analytics are being introduced to academia	Education	Examined request logs of self -hosted schools over a four-year period at United States of America	Proprietary software vendor	-	-	Lack empirical study

Table 2.1: Big Data Adoption Studies (Con't)

Study	Issue	Domain	Respondents	Data Collection	Measuring Instrument	Data Analysis Technique	Limitation
Wu, Li, Liu, & Zheng (2017)	Investigated the impact of BD and analytics on the health IT market	IT (Mobile healthcare market)	Consumers of two firms in China	Survey	-	Quantitative	Investigated the fully covered market
Gunasekaran et al. (2017)	Identified the influence of resources (top management and capability)	Firms	Manufacturing companies, consulting companies, electronic commerce companies, and technology at India	Survey	Five-point Likert scale	Quantitative	Limited to companies
Nguyen & Petersen (2017)	Identified the factors for Organizational Assimilation of BD	Organization	336 executive level employees of Norway companies	Survey	Seven-point Likert scale	Quantitative	Limited to medium to large enterprises, not Explored moderating effects

Table 2.1: Big Data Adoption Studies (Con't)

Study	Issue	Domain	Respondents	Data Collection	Measuring Instrument	Data Analysis Technique	Limitation
Verma & Bhattacharyya (2017)	Highlighted the factors affecting BD	Firms	22 different enterprisers and service providers in India	Face-to-face semi-structured interviews	-	Qualitative	Lack empirical study
Mneney & Van Belle (2016)	Examined the readiness of retail organization regarding BDA	Retail organizations	Respondents were 3 retailers, 3 vendors, and 2 IT service providers at South Africa	Semi-structured interviews	-	Qualitative	Only check the readiness situation
Soon, Lee, & Boursier (2016)	Studied factors affecting the adoption of BD	Private companies	40 employees from private companies of Malaysia	Survey	Five-point Likert scale	Quantitative	Findings are limited to the private company
Potter (2016)	Explored the factors that enhance BDA in SMMEs	Organization (SMMEs)	Senior management of South African companies	Semi-structured interviews	-	Qualitative	Sampling bias, respondent bias, research validity

Table 2.1: Big Data Adoption Studies (Con't)

Study	Issue	Domain	Respondents	Data Collection	Measuring Instrument	Data Analysis Technique	Limitation
Matsebula & Mnkandla (2016)	Highlighted the IS and innovation adoption in education and stress on TOE	Education	-	-	-	-	Lack of validity
Salleh & Janczewski (2016)	Analyzed the BD determinants among adopters and non-adopters	Organization	25 responses from organizations having more than 2000 employees in Auckland, New Zealand	Survey	Five-point Likert scale	Quantitative	The sample size was small
Almoqren & Altayar (2016)	Examined the factors affecting the adoption of BD in banks	Finance	54 participants who work in data processing, business intelligence and IT departments in Saudi banks	Survey	Five-point Likert scale	Quantitative	The sample size was small

Table 2.1: Big Data Adoption Studies (Con't)

Study	Issue	Domain	Respondents	Data Collection	Measuring Instrument	Data Analysis Technique	Limitation
Park, Kim, & Paik (2015)	Analyzed the factors related to TOE Influencing the BDA	Firms	5 experts having 10year of research experience from Korean firm	Survey	Nine-point Likert scale	Quantitative	Limited to BDA and its usage in firms only
Kang & Kim (2015)	To test the hypotheses based on the developed model	Firms	58 top management team or IS manager from the Korean firm	Survey	Seven-point Likert scale	Quantitative	Limited firms only
Yin (2015)	Developed BDA process framework	Companies (OEM)	Employees of Original Equipment Manufacturer (OEM) Company	Face-to face interviews	-	Qualitative	Limited to OEM companies
Chen, Kazman, & Matthes (2015)	Developed big data adoption model to clarify "why", and "how" questions	Companies	25 European enterprises of Hawaii, united states	Semi-structured interviews	-	Qualitative	Data collection is limited to interviews

Table 2.1: Big Data Adoption Studies (Con't)

Study	Issue	Domain	Respondents	Data Collection	Measuring Instrument	Data Analysis Technique	Limitation
Ochieng (2015)	Determined the factors affecting big data adoption in supermarkets	Supermarkets	5 leading Supermarket chains and the 3 independent supermarkets of Kenya	Survey	-	Quantitative	Limited to supermarkets

2.6 Big Data Adoption Models and Factors

Multiple studies have tested the level of adoption and usage of big data by incorporating various theoretical models.

Yadegaridehkordi et al. (2020) proposed a theoretical model based on Human-Organization-Technology fit (HOT-fit) and TOE. This study used Cost of adoption, Complexity, Compatibility, Relative advantage, Organization size, Management support, Organizational resource, Security and privacy concerns, External pressure, External support, Change efficacy and IT expertise as a variable.

Yadegaridehkordi, Hourmand, Nilashi, Shuib, Ahani, & Ibrahim (2018) study used TOE. The study used Competitive pressure, Government support and Partner pressure, Big data quality and integration, Complexity, Technology resources and Perceived benefits, Perceived costs, Management support, Change efficiency, and Human resources capability as model constructs. Sun, Cegielski, Jia, & Hall (2018) used DOI, TOE and IT as a base model. Similarly, Lai, Sun, & Ren (2018) study also employed TOE.

Lai, Sun, & Ren (2018) employed TOE to analyze the determinants of big data adoption in the organizational domain. This study used Technology (Perceived benefits, Technology complexity, and Data quality), Organization (Top management support, IT infrastructure/ capabilities, Financial readiness), Environmental moderators (big data adoption of competitors, Government policy and regulation) and Supply chain moderators (SC connectivity). In this study, data were collected from 210 IT managers in China. Verma, Bhattacharyya, & Kumar (2018) proposed a research model based on an extensive literature review on TAM. Verma, Bhattacharyya, & Kumar (2018) employed TAM. This study used

Perceived usefulness of big data adoption, Perceived ease of use of big data adoption systems, Attitude toward big data adoption systems, Behavioral intention to use big data adoption systems, big data adoption system quality, big data adoption information quality, Beliefs in the benefits of big data adoption systems.

Wu, Li, Liu, & Zheng (2017) used a two-dimensional product differentiation framework. Gunasekaran et al. (2017) used a resource-based view. Soon, Lee & Boursier (2016) used DOI and TAM. Another study conducted by Mneney & Belle (2016) used TOE and TTF.

Nguyen & Petersen (2017) employed DOI, TOE and TAM. This study used Relative advantage, Complexity, Compatibility, Security, Organizational Size, Top management support, IT expertise, Organizational resources, Competitive, External Support, Privacy, Big data assimilation, Initiation, Adoption decision, and Implementation. Verma & Bhattacharyya (2017), Almoqren & Altayar (2016) and Salleh & Janczewski (2016) studies also used TOE as a base model. However, Yin (2015) and Ochieng (2015) studies employed TOE and DOI. The summary of big data adoption models and factors is presented in Table 2.2.

Table 2.2: Big Data Adoption Models and Factors

Author	Model	Factors
Yadegaridehkordi et al. (2020)	HOT-fit and TOE	Cost of adoption, Complexity, Compatibility, Relative advantage, Organization size, Management support, Organizational resource, Security and privacy concerns, External pressure, External support, Change efficacy, IT expertise
Yadegaridehkordi, et al. (2018)	TOE	Big data quality and integration, Complexity, Technology resources and Perceived benefits, Perceived costs, Management support, Change efficiency, Human resources capability, Competitive pressure, Government support, Partner pressure
Sun, Cegielski, Jia, & Hall (2018)	DOI, TOE, IT	Innovation independent variables, Relative advantage, Cost of adoption Complexity, Compatibility, Trialability, Observability, Security, privacy and ethical concerns in collecting data, Trading partner readiness, Regulatory environment, IS fashion market, turbulence Institutional based trust, Business strategy orientation, IT organization structure, Business resources, IS strategy orientation, Firm size, Appropriateness, Human resources, Management support, Technology resources, Technology readiness, Decision-making culture, Change efficiency
Lai, Sun, & Ren (2018)	TOE	Technology (Perceived benefits, Technology complexity, Data quality) Organization (Top management support, IT infrastructure/ capabilities, Financial readiness) Environmental moderators (big data adoption, competitors, Government policy and regulation) Supply chain moderators (SC connectivity)

Table 2.2: Big Data Adoption Models and Factors (Con't)

Author	Model	Factors
Verma, Bhattacharyya, & Kumar (2018)	TAM	Perceived usefulness of big data adoption, Perceived ease of use of big data adoption systems, Attitude toward big data adoption systems, Behavioral intention to use big data adoption systems, Big data adoption system quality, Big data adoption information quality, Beliefs in the benefits of big data adoption systems
McLeod, Bliemel, & Jones (2017)	-	Big data, Analytics curriculum, Research agenda, Analytics, Business process curriculum
Wu, Li, Liu, & Zheng (2017)	Two-dimensional product differentiation framework	Two-dimensional product differentiation, Efficiency, Privacy, Risk and cost trade-offs
Gunasekaran et al. (2017)	Resource based view (RBV)	Connectivity, Information sharing, Top management commitment, Acceptance, Routinization, Assimilation, Organizational performance, Supply chain performance
Nguyen & Petersen (2017)	DOI, TOE, TAM	Technological (independent constructs) (Relative advantage, Complexity, Compatibility, Security) Organization (Organizational Size, Top management support, IT expertise, Organizational resources) Environment (Competitive, External support, Privacy) Big data assimilation (Initiation, Adoption decision, Implementation)

Table 2.2: Big Data Adoption Models and Factors (Con't)

Author	Model	Factors
Verma & Bhattacharyya (2017)	TOE	Technological (Complexity, IT assets, Compatibility) Organizational (Top management support, Organizational data environment Perceived cost) Environmental (External pressure, Industry type)
Almoqren & Altayar (2016)	TOE	Technological (Wireless technology, System integration, Internal and External control, IT infrastructure, Interpretation of unstructured data) Organizational (Information management, Change management, Top management, Organizational structure, Human resource) Environment (Information intensity, New market strategies, Competitive pressure)
Salleh & Janczewski (2016)	TOE	Technological (Perceived complexity, Perceived compatibility) Organizational (Top management support, Information security culture, Organizational learning culture) Environmental (Security/Privacy regulatory concerns, Risks in outsourcing), Organizational intention to adopt big data solutions
Mneney & Belle (2016)	TOE, TTF	Technology (Knowledge about big data, Relative advantage, Complexity, Availability of big data tools) Organization (Management support, Human resources, Financial resources, Governance, Organizational culture) Task-technology fit (Big data uses cases)
Soon, Lee, & Boursier (2016)	TAM, DOI	Perceived usefulness, Perceived benefit, Predictive analytics accuracy, Perceived ease of use, Perceived risk, Training, Big data adoption

Table 2.2: Big Data Adoption Models and Factors (Con't)

Author	Model	Factors
Potter (2016)	-	Evidence based, Entrepreneurial orientation
Matsebula & Mnkanla (2016)	TOE	Education, Big data, Technological innovation, Organizations, Decision making, Ethical Issues
Kang & Kim (2015)	TOE	Perceived direct benefit, Perceived indirect benefit, Low perceived financial readiness, Perceived IS Competence, Perceived industrial pressure, Perceived government policies
Yin (2015)	TOE, DOI	Relative advantage, top management support and competitive pressure, marketing effort
Chen, Kazman, & Matthes (2015)	--	Big data adoption model, Enterprise emerging IT innovation adoption, Firm level adoption factors, Deployment gap, Complexity tolerance
Ochieng (2015)	TOE, DOI	Complexity, Trialability, Observability, Compatibility, Right infrastructure, Technical skills, Relative advantage

2.7 Models and Factors used for Technology Adoption in Higher Educational Studies

Multiple educational studies have successfully used DOI and TOE for innovation adoption. Qasem et al. (2020) and Hiran & Henten (2019) used TOE and DOI integration to analyze the factors that may hinder the adoption of cloud computing in the higher education sector. Alajmi, Arshah, Kamaludin, & Al-Sharafi, (2018) observed cloud-based e-learning adoption by incorporating TOE and DOI. In this study, data was collected from IT managers of Gulf Cooperation Council (GCC) universities. Another study conducted by Tarhini, Al-Gharbi, Al-Badi, & AlHinai (2018) utilized TOE to analyze the factors affecting innovational adoption in higher educational institutions. Data was collected from IT decision-makers working in four higher educational institutions in Oman (Table 2.3).

Sabi, Uzoka, Langmia, Njeh, & Tsuma (2017) analyzed the adoption of cloud computing in education. Data was collected from ICT staff administrators at universities in sub-Saharan Africa. This study used the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique as a statistical tool to analyze the data. Mokhtar, Al-Sharafi, Ali, & Al-Othmani (2016) and Tashkandi & Al-Jabri (2015) used TOE to explore the adoption of technology in higher education. Data was collected from ICT managers and heads of departments. Makoza (2015) applied TOE, DOI to analyze cloud computing adoption in Higher Education Institutions.

To summarise, TOE and DOI can be used to explore the different innovational adoption in various educational contexts. However, most studies were quantitative and used surveys for data collection. Moreover, data is mainly collected from IT

managers' perspectives. The summary of models and factors used in adoption in educational studies is presented in Table 2.4.

Table 2.3: Adoption in Higher Educational Studies

Study	Issue	Respondents	Data Collection	Data Analysis Technique	Statistical tools
Qasem et al. (2020)	Determinants of cloud computing adoption in Higher Education Institutions	Institutional managers	Survey	Quantitative	PLS-SEM
Hiran et al. (2019)	Examined cloud computing adoption in the higher education sector	Faculty members, staff and students	Survey	Quantitative	SPSS
Alajmi et al. (2018)	Analyzed current State of Cloud based e-learning adoption	IT managers of GCC universities	Survey	Quantitative	SPSS
Tarhini et al. (2018)	Analyzed the factors affecting the innovative adoption in Higher Educational Institutions	IT decision-makers working in four higher educational institutions in Oman	Survey	Quantitative	AMOS 22.0
Sabi et al. (2017)	Examined impact of cloud computing at universities	ICT staff, administrators at universities of sub-Saharan Africa	Survey	Quantitative	PLS-SEM

Table 2.3: Adoption in Higher Educational Studies (Con't)

Study	Issue	Respondents	Data Collection	Data Analysis Technique	Statistical tools
Mokhtar et al. (2016)	Investigated adoption of technology in higher education	ICT managers, CIO or deputies of higher educational accredited institute of Malaysia	Survey	Quantitative	-
Tashkandi & Al-Jabri (2015)	Analyzed Innovative adoption in Higher Education Institutions	Head of IT department of Saud Arabia	Survey	Quantitative	PLS-SEM
Makoza (2015)	Explored cloud computing adoption in Higher Education Institutions	IT Managers from Higher Education Institutions of Malawi	Survey	Quantitative	-

Table 2.4: Models and Factors used Adoption in Higher Educational Studies

Author	Model	Factors
Qasem et al. (2020)	TOE, DOI	Compatibility, Competitive Pressure, Complexity, Cost Savings, Vendor Support, Technology Readiness, Top Management Support, Security
Hiran et al. (2019)	TOE, DOI	Polities, Socio-economics, Government Incentives, Relative Competitive, Changes of the Industry Structure, Government Regulation, Competitive Pressure, Generation of New Business Opportunities, Technological Infrastructure, Financial Readiness, Commitment of Resources, Long-term Vision and Establishment of Goals, Organizational Readiness, Top Management Support, Efficiency and Flexibility, Ease of Use and Data Integration, Cost and Manageability, Compatibility, Relative Advantage
Alajmi et al. (2018)	TOE, DOI	Relative Advantage Fit, Decision makers, Information Integrity, Information Formality, Information Control, Information Proactiveness, Complexity, Compatibility, Cost Reduction, IT Readiness
Tarhini et al. (2018)	TOE	Top Management Support, Relative Advantage, Attitudes towards change, Technology Readiness, Complexity, Government Regulation, Peer Pressure, Data Concerns, Compatibility, Vendor lock-in and External Expertise
Sabi et al. (2017)	DOI	Actual usage, Awareness, Compatibility, Costs, Complexity, Data security, Ease of Use, Intent to Adopt, Infrastructural requirement, Observability, Perceived Usefulness, Relative Advantage, Results demonstrable, Risk, Socio-cultural Values, Trialability

Table 2.4: Models and Factors used Adoption in Higher Educational Studies (Con't)

Author	Model	Factors
Mokhtar et al. (2016)	TOE	Relative Advantage, Complexity, Compatibility, Top Management Support, Institution Size, Adoption Plan, Environment Service Provider, Government Support
Tashkandi (2015)	TOE	Relative Advantage, Compatibility, Privacy Concerns, Complexity, Vendor lock-in, Top Management Support, Regulatory policies, Government policies, Peer pressure
Makoza (2015)	TOE, DOI	Internet Connectivity, IT Labor Market, Political Stability and Services of Network Providers, Top Management Support, Skilled Staff, Size, E-mail services, IT services, Government Policy, Stage of adoption (early or late)

2.8 Higher Education of Pakistan

In Pakistan, higher education alludes to education above grade twelve or intermediate. In Pakistan, higher education is supervised by HEC (Zahid, Hooley & Neary, 2020). Currently, higher education institutions are comprised of a "university degree" administered by the HEC. Pakistan has two types of universities: public and private. The focus of both sectors is highly related to science, technology, and medicine. Both sectors are providing technology-based facilities to their enrolled students. Most of the higher education institutes are bunched in the territory of Punjab. Most institutes are for the public sector.

2.8.1 Emergence of Technology Adoption in Higher Education Institutions of Pakistan

In Pakistan, ICT-based, degree-level education was started in late-90 (Butt, Siddiqui, Soomro, & Asad, 2020). Universities started to put efforts into incorporating computers and internet services to facilitate the students (Asad, Hussain, Wadho, Khand, & Churi, 2020). Subsequently, institutions adopted high-speed internet, developed computer labs, constructed video conference rooms, integrated modern technology with traditional classrooms, provided facilities to access digital libraries and implemented an e-learning environment to promote overall learning and education. Pakistan's government has significantly contributed to the spread of technology in the education sector and introduced the prime minister laptops scheme for deserving and merit-based students. The government of Pakistan has distributed more than 300,000 free laptops to students (Gill, Aftab, Rehman, & Javaid, 2019). Consequently, books and classrooms are now being replaced with laptops for learning (Asad, Hussain, Wadho, Khand, & Churi, 2020).

2.8.2 Virtual University

One public institution that offers higher education programmes with the help of electronic media is known as a "Virtual University" (Beilin, Soina, Dyachenko, & Semenova, 2021). The common objective of virtual universities is to provide high-quality education, easy to access (anytime, anywhere) and cost-effective (Malik, 2020). The primary purpose of the virtual pedagogical setup is to facilitate three users: administrators, students, and instructors in their respective fields (Maurya, 2018).

2.8.3 Virtual University of Pakistan

The Virtual University (VU) of Pakistan is a higher education institution. The VU is the first institution in Pakistan based on innovative technology (Malik, 2020). The government of Pakistan set it up as a public area, a not-for-revenue university. VU provides quality education for the socio-financial improvement of the country. Aside from character development, it provides the human resources required for exploration, advancement, development, and public turn of events. Furthermore, comprehensive and uniform admission to higher education is critical for leading the country toward monetary and technological advancement.

VU is an electronic learning based university. It has adopted a hybrid model to deliver education. It provides classrooms and ICT-based laboratories. It allowed free-to-air satellite transmissions and the Internet. Students used LMS and email to interact with the faculty and administration.

The course hand-outs and all supporting material for designed courses are accessible to students through the portal. The recorded lectures are also available online for all students beyond geographical restrictions. One of the significant difficulties the education sector faces is the absence of qualified staff. Successful usage of ICT provides a practical answer to this issue while keeping up with the most noteworthy and internationally adequate instructional principles.

The VU permits students to follow it through projects, paying little heed to their actual location. By distinguishing the country's top teachers, paying little heed to their institutional affiliations, and mentioning them to create and convey hand-made courses. VU provides the best courses to every student in the country (Malik, 2017). VU opened its entryways in 2002. In a short period, it has reached more than 100 urban areas of the country, with more than a hundred and ninety related campuses giving infrastructure backing to the students (Malik, 2020). The location and number of campuses are given below.

- Three campuses in Azad Kashmir
- Four campuses in Balochistan
- Three campuses in Islamabad Capital Territory
- Two campuses Gilgit Baltistan
- Fifteen in Khyber Pakhtunkhwa
- One hundred and forty-eight in Punjab
- Twenty-five in Sindh

2.9 Research Gaps in the Literature

The literature showed that TOE and DOI had been extensively used for big data adoption in firms, organizations, and companies. In big data adoption studies, data

were collected from IT managers, IT service providers, IT departments, and IS managers. The majority of the studies used surveys for data collection and were analyzed through quantitative techniques. However, most of the studies lacked empirical research (Matsebula & Mnkandla, 2016; Sun, Cegielski, Jia, & Hall, 2018). The extant literature (Table 2.1) shows there is still a lack of big data adoption theoretical model in the higher education sector. Therefore, this research gap can be addressed by identifying the factors that affect big data adoption, developing and validating a theoretical model for big data adoption in the higher education sector. The theoretical framework for big data adoption in the higher education sector can be helpful to analyzing and solve multifarious problems to meet future needs.

2.10 Summary

This chapter gives an overview of big data. Then, it presents the discussion on big data adoption and benefits. It also discussed the theoretical models used for technology adoption. It also provides a comprehensive picture of the state of the art of big data adoption. This chapter uncovers the big data adoption models and factors. Furthermore, the big data adoption factors were explained. The models and factors used for adoption in higher education studies were also discussed. It also presents the higher education setup of Pakistan and the emergence of technology adoption in the higher education sector of Pakistan. Finally, the research gap is the literature portrayed in this chapter. The next chapter describes in detail the research methodology of this study.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

Research methodology is the way through which scientists need to direct their research. It shows how these analysts figure out their concerns and present their outcome from the information acquired during the investigation period.

This chapter starts with research paradigms. The details of the positivist paradigm, interpretivist paradigm, critical paradigm and finally selected paradigm are also discussed. The next section presents the research design. Further, the sampling technique, participants, sample size and data collection are also presented. In the next section, questionnaire development is described. Under this section, the details of questionnaire design, the information needed, type of interview, the content of the individual question, design of questions to respondent inability and unwillingness to answer, question structure, question-wording, questions in order, form and layout, reproduce the questionnaire and how to clean the questionnaire were described. Moreover, measurement items were discussed in detail and the content validity was calculated based on an expert's opinion. This is followed by data analysis methods. Finally, the pilot study was conducted to confirm the validity and reliability of the questionnaire before the main study.

3.2 Research Paradigms

The word paradigm refers to a "philosophical perception" (Johnson & Onwuegbuzie, 2004). However, few researchers used this word as a "pattern"

(Denscombe, 2008). In the educational realm, the word "paradigm" is used to describe a perspective. This perspective is the viewpoint, or thinking, way of thinking, or shared convictions that illuminate the translation of information or data (Leedy & Ormrod, 2005; Hart, 2010). It clarifies that an examination worldview innately mirrors scientists' convictions (Ohlsson, 2012). It shapes the theoretical convictions and rules that shape how a specialist sees the world and deciphers and acts within it (Denscombe, 2014).

Building a theory is dependent on a worldview's thought, for example, how society creates from a worldview (Mertens, 2014). It is a hypothetical point of view that is shared and perceived by the local exploration area of an order that depends on the past accomplishments of the control (Rehman & Alharthi, 2016). This is connected to the detailed study of a theory, yet for the most part, it is the method of moving toward a theory that makes it conceivable to characterize the theoretical and methodological instruments to be utilized to advance its hypothesis (Morgan, 2007).

Standards are also important because they provide convictions and point to researchers in the right direction (Teddle & Yu, 2007; Johnson, Onwuegbuzie, & Turner, 2007). It impacts what ought to be contemplated, how it ought to be considered, and how aftereffects of the investigation ought to be deciphered (Blaikie & Priest, 2019; Hennink, Hutter, & Bailey, 2020). The field characterizes a paradigm as an essential allowance of expectations or perspective that aids research activity or an examination (Teddle & Tashakkori, 2006; Thorne, 2016).

So far, various paradigms have been proposed by field specialists (Onwuegbuzie & Collins, 2007). However, Candy (1989) recommended that all paradigms be

gathered into three fundamental scientific categorizations: Positivist, Interpretivist, and Critical standards (Teddlie & Yu, 2007; Jones, Torres, & Arminio, 2013). However, different studies proposed a fourth paradigm known as the "Pragmatic," which incorporates elements from the first three.

3.2.1 Positivist Paradigm

The Positivist paradigm defines a worldview for research, which is grounded in what is known in research methods as the scientific method of investigation (Hesse-Biber, 2010). The positivist worldview investigates the social truth. It depends on the possibility that one can best acquire a comprehension of human conduct through perception and reason (Thorne, 2016).

Expressed in an unexpected way, just level-headed, perceptible realities can be the reason for science. As indicated by the positivist worldview, genuine information depends on experience and can be obtained by perception and analysis (Johnson, Onwuegbuzie, & Turner, 2007). Positivist scholars lean unequivocally on determinism, observation, stinginess, and over-simplification (Denscombe, 2014; Gough, Oliver, & Thomas, 2017).

With these presumptions of science, a definitive objective is to coordinate and arrange discoveries into a significant example or hypothesis which is viewed as conditional and not a definitive truth. A hypothesis is dependent upon amendment or alteration as a new proof is found (Morgan, 2007).

The Positivist worldview accordingly arranges the information age measure with the assistance of evaluation, which is vital for improving accuracy in the depiction of boundaries and the acumen of the relationships among them. Nonetheless, the theoretical claims should respect the positive research, which can be clarified as far

as logical laws. A fascinating component of positivism is that it acknowledges extraordinary and unique information for research purposes (Gough, Oliver, & Thomas, 2017).

Positivists accept that information can be "uncovered" or "found" using a logical strategy. The "found" information empowers us to give potential clarification of the reasons for things that occur on the planet. A positivist methodology underscores experimentation, perception, control, estimation, dependability, and legitimacy in examination cycles. This infers a quantitative method (Ochieng, 2009). Genuine information depends on experience and can be acquired by perception and examination.

Positivists expect that the fact of the matter is dispassionately given and is quantifiable, utilizing properties that are autonomous of the analyst and their instruments. The information is level-headed and quantifiable (Johnson, Onwuegbuzie, & Turner, 2007). Positivistic scholars receive logical techniques and organize the information age measure with the assistance of evaluation. It improves accuracy in the depiction of boundaries and, what's more, the relationship among variables.

Positivists contend that the logical examination strategy produces exact, certain, methodical, and hypothesized responses to the exploration question or speculation (Rehman & Alharthi, 2016). It additionally recommends that the utilization of the logical technique gives answers that are unbiased and specialized and would thus be able to be universalized and summed up to all chronicled and social settings (Östlund, Kidd, Wengström, & Rowa-Dewar, 2011). The experimentation, observation, and reason based on experience ought to be the basis for

understanding human behaviour, and therefore, it is the only legitimate means of extending knowledge (Williams, 2007).

The scientific methods are based on the logical technique, which includes a cycle of experimentation that is utilized to investigate perceptions and answer questions (Denscombe, 2014; Gough, Oliver, & Thomas, 2017). It is used to look for circumstances and logical results and their connections with nature (Onwuegbuzie & Leech, 2006; Greene, 2008).

3.2.2 Interpretivist Paradigm

Interpretivism, also called interpretivist, includes scientists deciphering components of the examination; along these lines, interpretivism incorporates human premium into an investigation (Collins, Onwuegbuzie, & Jiao, 2007). Likewise, interpretive scientists accept that admittance to the real world (given or socially developed) is just through friendly developments like language, awareness, shared implications, and instruments.

The advancement of interpretivist reasoning depends on the scrutiny of positivism in sociology. In like manner, this way of thinking stresses subjective investigation over quantitative examination (Johnson, Onwuegbuzie, & Turner, 2007; Collins, Onwuegbuzie, & Jiao, 2007). Interpretivist research is guided by the analyst's allowance of faith-based expectations and sentiments about the world and how it ought to be perceived and examined (Östlund, Kidd, Wengström, & Rowa-Dewar, 2011).

In the interpretive worldview, information is comparative with specific conditions recorded, fleeting, social, abstract, and exists in different structures as portrayals of the real world (understanding by people)" (Morgan, 2007). Interpretivists

acknowledge numerous implications and methods of knowing and recognizing target reality can never be caught (Mackenzie & Knipe, 2006). It just knows it through portrayals.

The interpretive worldview centres, basically around perceiving and portraying the significance of human encounters and activities. All interpretive exploration should hold fast to a typical arrangement of standards, as depicted underneath. Social phenomena should be concentrated within their specific context (Rehman & Alharthi, 2016).

Since interpretive examination expects that social wonders are arranged inside and can't be segregated from their social setting, understandings of such marvels should be grounded inside their socio-verifiable setting (Collins, Onwuegbuzie, & Jiao, 2007). Researchers are frequently installed in the social setting that they are contemplating and are viewed as a feature of the information assortment instrument. It utilizes their observational abilities, their trust in the members, and their capacity to extricate the right data. Further, their own experiences, information, and encounters in social setting are basic to precisely deciphering the marvel of interest (Kivunja & Kuyini, 2017).

Interpretive exploration is frequently not worried about looking for explicit answers yet with comprehension or "figuring out" a unique social interaction as it unfurls after some time (Denscombe, 2014; Gough, Oliver, & Thomas, 2017).

As a result, such an investigation necessitates the active participation of the scientist at the investigation site for an extended period of time in order to capture the entire development of the revenue marvel (Kivunja & Kuyini, 2017).

Interpretive understanding is an iterative cycle of moving to and from bits of perceptions (text) to the aggregate of the social marvel (setting) to accommodate their evident disagreement and build a hypothesis that is steady with the assorted abstract perspectives and encounters of the inserted members (Rehman & Alharthi, 2016). Information is gathered in an interpretive examination utilizing an assortment of procedures. The most frequently utilized procedure to interviews. Meeting types and procedures are talked about in detail in a previous section on review research (Östlund, Kidd, Wengström, & Rowa-Dewar, 2011; Denscombe, 2014; Gough, Oliver, & Thomas, 2017).

As discussed previously, case research is a serious longitudinal investigation of wonder at least. It is a destination to determine definite, contextualised deductions and understand the powerful interaction and basic marvel of revenue. Case research is an excellent research strategy because it can be used to generate hypotheses in an interpretive manner (Denscombe, 2008). The case research examines the two methods inside and out and gives illustrative models (Rehman & Alharthi, 2016).

The focal undertaking of the interpretivist paradigm is to comprehend the abstract universe of human experience (Östlund, Kidd, Wengström, & Rowa-Dewar, 2011). This paradigm comprehends and deciphers what the subject is thinking or the importance of the specific situation (Akyol & Garrison, 2008). Thus, the key precept of the interpretivist paradigm is the truth that is socially developed (Teddle & Yu, 2007). In this paradigm, it has two criteria, namely trustworthiness and authenticity (Greene, 2008). However, in educational research, these criteria are not acceptable (Ellis, 2014). In the interpretivist paradigm, case study and grounded theory are wide choices (Denscombe, 2008).

3.2.3 Critical Paradigm

This paradigm explores social equity issues and tries to address the political, social, and monetary issues that lead to social persecution, strife, battle, and force structures (Jones et al., 2013). Yvonne (2010) explains that a critical paradigm is any examination that challenges those customary information bases and approaches, whether quantitative or subjective, that makes a guarantee of logical objectivity.

The critical paradigm endeavours to uncover the socio-authentic explicitness of information and to reveal insight into how specific familiarities create primary relations of disparity and persecution (Teddlie & Tashakkori, 2006; Thorne, 2016). The basic hypothesis is concerned with the implications of encounters as it identifies with gender orientation, race, class, and different sorts of social mistreatment.

Scientists following basic hypothesis strategies accept that social truth is generally made and that it is delivered and imitated by individuals (Denscombe, 2008). In spite of the fact that individuals can intentionally act to change their social and financial conditions, basic scientists perceive that their capacity to do so is compelled by different types of social and political control.

The primary assignment of basic examination is viewed as being one of social evaluation, whereby the prohibitive and distancing states of affairs are uncovered. Basic exploration centres on the challenge, strife and inconsistencies in contemporary society and tries to be emancipator. It should assist with wiping out the reasons for estrangement and mastery.

Awareness and personality are framed within the political field of information (Gough, Oliver, & Thomas, 2017). Scholars argue that the attempt to avoid values, recorded conditions, and political considerations in research is perplexing (Rehman & Alharthi, 2016). Specialists who use hypotheses assert that significant sociological information emerges from the examination of the social design and frameworks as revealed by examination of public discourse. The scientist exposes the current discussions in the public eye and examinations.

As far as the framework inside which is workable with the point of unveiling the force connections inside the framework. Its designs so the severe idea of the framework can be uncovered. Strife (for instance, racial, class, strict or gender struggle) and imbalance are critical to understanding the elements of human relations (Ochieng, 2009).

A critical paradigm has three sorts of information: specialized interest, down-to-earth interest, and liberating interest. Specialized revenue is worried about the control of the actual climate, which produces observational and insightful information (Teddlie & Tashakkori, 2006). A viable premium is concerned with understanding the importance of circumstance, which produces hermeneutic and recorded information (Thorne, 2016).

Liberating revenue is concerned about the arrangement of development and progression, creates basic information, and is apprehensive about uncovering states of requirements and control. The understanding of the instructive situation is dependent on the internal environment, such as experience.

The hypothetical information and presumptions impact the perception (Yvonne, 2010). These variables make philosophical casings of reference that go about as the

focal points through which the world is visible. Since it looks to change the governmental issues in order to go up against social mistreatment and improve social equity in the circumstance (Blaikie & Priest, 2019).

This paradigm expects a value-based epistemology and metaphysics of recorded authenticity. It particularly identifies with mistreatment a procedure that is dialogic, and axiology that regards social standards (Collins et al., 2007). In the critical paradigm, cultural studies and race theory-based methods are applied (Mertens, 2014).

3.2.4 Discussion on Selected Paradigm

The positivist paradigm is adopted for this research study. It is the most recommended paradigm for educational research, attempting to decipher perceptions regarding realities or quantifiable elements (Yin, 2018).

Research in this paradigm depends on deductive rationale. It is related to developing hypotheses, testing theories, offering operational definitions and numerical conditions, counts, extrapolations and articulations, to infer ends (Teddlie & Tashakkori, 2006). The Positivist paradigm is primarily acceptable in educational research (Small, 2011; Ellis, 2014). The positivist is mostly validated by applying four principles: internal validity, external validity, reliability, and objectivity (Burns & Bursn, 2000).

The internal validity degree to which the outcomes acquired in an investigation are inferable from the independent factor that clarifies their event (Sovacool, 2014). Conversely, external validity alludes to how much the outcomes got in an examination can be summed up in different settings (Richey & Klein, 2007).

Reliability is a quality that is characterized as the degree to which results are consistent after some time (Yin, 2006). Objectivity is the point where an instrument is viewed as solid (Collins et al., 2007). In the positivist paradigm, experimental and mostly survey-based research are recommended.

3.3 Research Design

There are three significant research methods (Abell, Appleton, & Hanuscin, 2013). These are quantitative, qualitative, and mixed-method research (Packer, 2017). However, most researchers categorized research methodology into two categories, namely qualitative and quantitative (Richey & Klein, 2007; Neuman, 2013).

Qualitative research is used to understand the reason, views and incentives (Williams, 2007). This could be helpful to recognizing the actual problem (Richey & Klein, 2007). Qualitative research depends on the assortment of subjective information (Thorne, 2016). Qualitative data is based on open-ended information, focus group or in-depth interviews and observations (Bernard & Bernard, 2012).

Quantitative research fundamentally depends on the assortment of quantitative information (Greene, 2008). Quantitative research accentuates the purpose, quantity/measurements and is based on statistical or numerical analysis (Bernard, 2017). Quantitative research was more able to generalize the results (Onwuegbuzie & Collins, 2007; Mertens, 2014). Quantitative methods involve data collected through close-ended information, surveys, experiments and different rating scales etc.

The quantitative method involves data collection based on a hypothesis or theory, and it is followed by statistical analysis (Richey & Klein, 2007; Hart, 2010). This type of data is usually based on scores collected through questionnaires to test the

hypotheses (Burns & Burns, 2000). Mix method research includes the blending of quantitative and qualitative strategies or other paradigm attributes (Abell et al., 2013). It incorporates both qualitative and qualitative research methods (Jick, 1979; Denscombe, 2008). Therefore, to obtain the objective of this research, a quantitative approach is employed to quantify the data and test the hypotheses statistically (Blaikie & Priest, 2019).

In Pakistan, large numbers of universities are using technology to enhance traditional learning. The VU of Pakistan is the pioneer institution that is entirely based on innovative ICT facilities. VU students are using the latest technology for different educational purposes. Consequently, a huge amount of digital data is produced from various educational and learning activities. This data is managed by IT staff at various levels. Therefore, data will be collected by network administrators, database administrators, and IT managers of VU campuses.

This research is based on three major phases (Figure 3.1). The first step is information requirements. In this step, a comprehensive review is conducted to identify the research gap leading to the research problem, research objectives, and scope of this study. The review of the literature and research gap is presented in Chapter 2. The research problem, questions, and scope are presented in Chapter 1. Furthermore, factors were extracted from existing literature reviews and developed model for this study. The second phase is model development and data collection. The identified factors and model and hypotheses development are presented in Chapter 4. Moreover, phase, sampling technique and participant, sample size and data collection and questionnaire development steps were described (Chapter 3). A pilot study was conducted before the start of the main study. The pilot study was conducted on a small scale. However, in the main study, data was collected to a

large extent (Figure 3.1). The third step is model validation. In this step, the model is assessed statistically by applying SEM. The model validation is presented in Chapter 5.

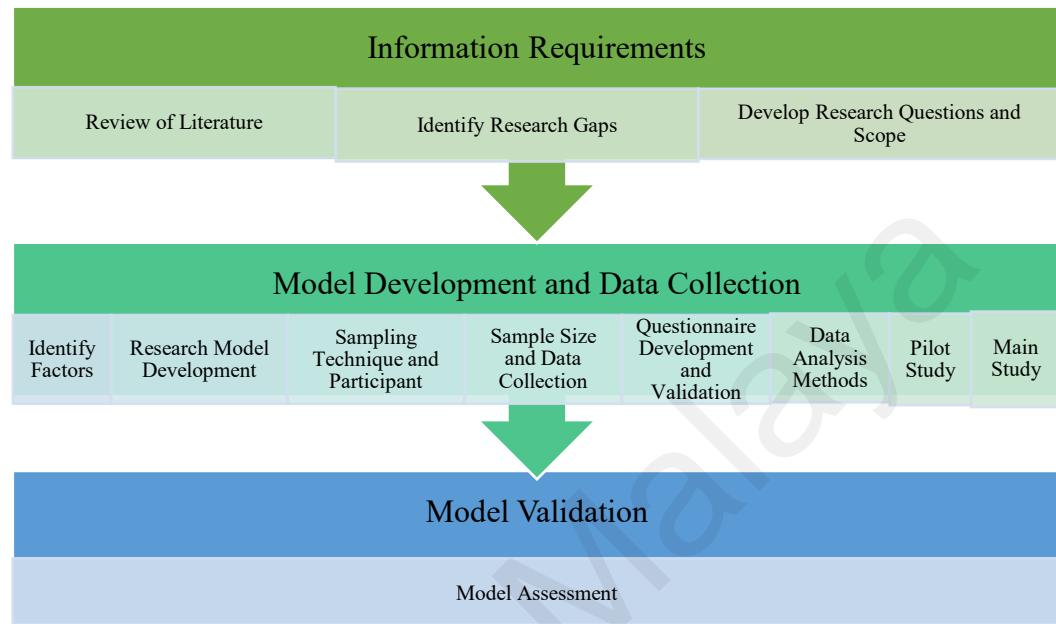


Figure 3.1: Research Steps

3.3.1 Systematic Literature Method

A systematic literature review was conducted for the first phase (information requirements). Activities involved are reviewing the literature, identifying a research problem, and developing research questions and scope. An effective review is based on an analysis of the literature, which finds the limitations and research gaps in a particular area. A systematic review can be defined as a process of analyzing, accessing, and understanding the method. It explains the relevant research questions and areas of research. The essential purpose of conducting a systematic review is to explore and conceptualize the extant studies; identify the themes, relations, and gaps; and describe the future directions accordingly. Thus, the identified reasons match the aim of this study.

Articles were searched and collected by using different search engines and databases. During the initial search process, it was found that the majority of research studies were present in IEEE Xplore (408), Science Direct (96), Emerald Insight (129), AIS Electronic Library (98), Taylor and Francis (46), ACM Digital Library (73) and Springer Link (57). In addition, the following keywords were used to extract relevant papers: "big data", "big data adoption" , "big data analytics" , "big data acceptance", and "big data plus TOE/DOI/TAM". The following criteria were used for the paper selection: (1) pertinent to the topic (big data adoption models, influencing factors, and challenges) written in the English language; (2) published between the years 2015 and 2020; (3) the mentioned search words should be in the paper title or in the keywords list; (4) available to download as a full article.

After the initial comprehensive database search, 907 research papers were found. Out of 907 papers, 589 articles were available for download. All 271 papers were downloaded and studied thoroughly, while the inclusion and exclusion criteria were applied for the final selection. Additionally, keywords were examined by reading the paper's title, abstract, introduction, and conclusions. One hundred ninety-five were excluded because most of these papers highlighted the database models for big data adoption (Figure 3.2). Papers that were not published in journals and conferences were also eliminated. Meanwhile, uncompleted and non-English studies were excluded.

In total, 76 eligible articles were double-reviewed, and 62 articles were removed from the final selection because they were unrelated to the actual study area. Their actual focus was not on big data adoption and its theoretical model. Before the final selection phase, the snowball technique was used to give a more comprehensive review of 'big data adoption' studies. The manual search method was applied to the reference list of each 'eligible' paper. Through screening, 8 studies were found from Google scholar. However, it was studied and later excluded because its focus was not on big data adoption. The Google Scholar search was only used for a second search (S2) but was not applied for the initial search. Finally, the selected articles were from IEEE Xplore (3), Science Direct (6), Emerald Insight (3), AIS Electronic Library (2), Taylor and Francis (1), and Google Scholar (6). After scrutiny, it was finally found that big data adoption-related studies started in 2015 and continued until 2020. Thus, 21 highly relevant articles were included in this study (Table 2.1 and Section 2.5). This helped to identify the first research objective of this study.

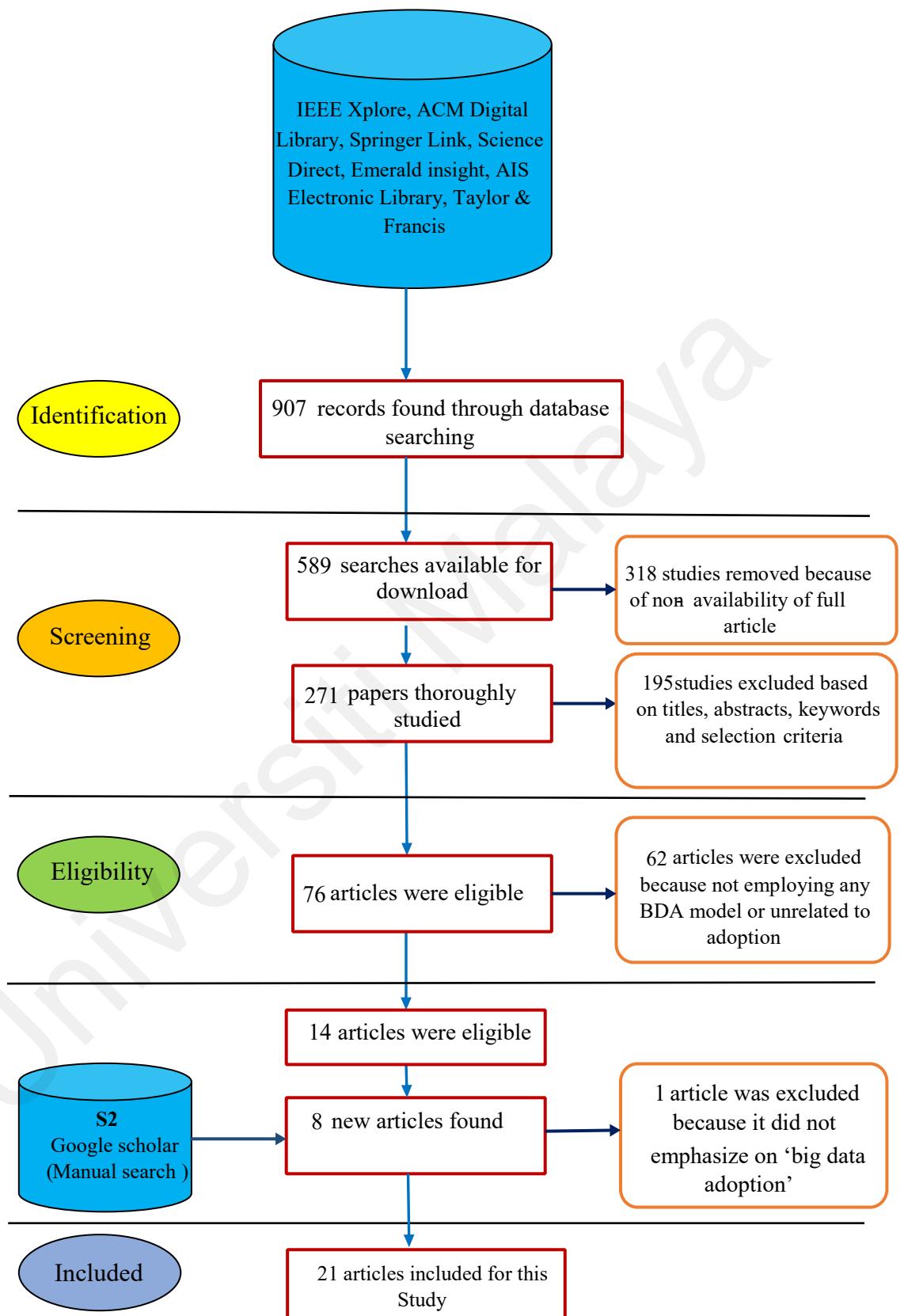


Figure 3.2: Articles Selection Process

3.4 Sampling Technique and Participants

Sampling is the procedure of choosing individuals or a subset of the populace to make factual deductions from them and gauge the quality of the entire populace (Hennink et al., 2020). Distinctive sampling techniques are broadly used by researchers in statistical surveying (Blaikie & Priest, 2019). It helps to explore the whole populace to gather significant bits of knowledge (Thorne, 2016).

Purposive sampling refers to selective sampling in which members of the population to participate in the study were selected judgmentally. The decision to adopt big data is made by management (Lai, Sun, & Ren, 2018).

Therefore, the managerial side needs to select purposefully. A purposive sampling technique was employed in this study. The main goal of using purposive sampling was to focus on the IT management staff of VU campuses that were directly handling the networking and data-related issues that facilitate the ICT services. Therefore, in this study, data was collected from the managerial side of VU campuses through an online quantitative survey. The participants were IT administrators, campus administrators, network administrator/associate network administrators, system administrators, and database administrators.

3.5 Sample Size and Data Collection

In order to collect the data, a questionnaire was created using a Google Form, and the generated link was mailed to respective respondents at VU campuses. The details of VU campuses and campus management staff were present on the VU official portal, campus sites, and Google search engine. The VU campuses were present all over Pakistan to spread high-quality education with convenience. The detailed instructions were mentioned at the start of the questionnaire. The

respondents were requested to participate in the survey. All ethical principles regarding confidentiality were strictly followed. The findings will never be attributed to any individual. Only aggregated results will be reported. A reminder email was sent to the respondents every two weeks. The data collection process lasted for four months.

A total of 350 emails were sent, and 230 responses were received. However, 35 responses were excluded as they did not qualify based on the opening question of the questionnaire. To ensure the adequacy of the sample size, the Hair et al. (2021) rule of sample size calculation was applied. According to Hair et al. (2021), the sample size should be at least ten times the largest number of structural paths directed at a particular construct in the structural model. G*power 3.1.9.4, priori power analysis was also performed to confirm the sample size. The Hair et al. (2021) rule of sample size calculation and G* power analysis ascertained that a total of 195 received responses is sufficient to examine and validate the proposed model. Previous studies also confirmed the adequacy of this sample size (Lai, Sun, & Ren 2018; Verma, Bhattacharyya, & Kumar, 2018). A total of 195 received responses are sufficient to examine and validate the proposed model.

3.6 Questionnaire Development and Validation

This study utilized a questionnaire to gather data from respondents. To develop the questionnaire, this study followed Malhotra's (2010) questionnaire design process. In this research, a structured questionnaire was formulated in two sections. The first section was based on the participants' demographic information. However, the opening question starts with the respondent's qualifying question. The second section consisted of questions related to latent variables.

A five-point Likert scale extending from "Strongly Disagree (1)" to "Strongly Agree (5)" was utilized. Altogether, 51 questions were selected from the related studies and were amended to match the context of this study (Appendix). The 15 questions were formulated for technology-related constructs (Premkumar and Roberts, 1999; Alshamaileh, 2013; Tehrani, 2013). The organization section contained a total of 20 questions (Premkumar and Roberts, 1999; Tehrani, 2013; Boonsiritomachai, 2014). The environmental section comprises a total of 12 questions (Premkumar and Roberts, 1999; Ochieng, 2015; Khater, 2017).

3.6.1 Instrument Development

A questionnaire is an instrument that contains a set of questions. It interprets the information in the form of questions. It is used to obtain information from respondents. It is mostly delivered through surveys (Burns & Burns, 2000). Respondents provide the information by giving the answers to questions. Questions must be focused, brief, simple, and easy to understand for respondents. This study follows Malhotra's (2010) questionnaire design process (Figure 3.3).

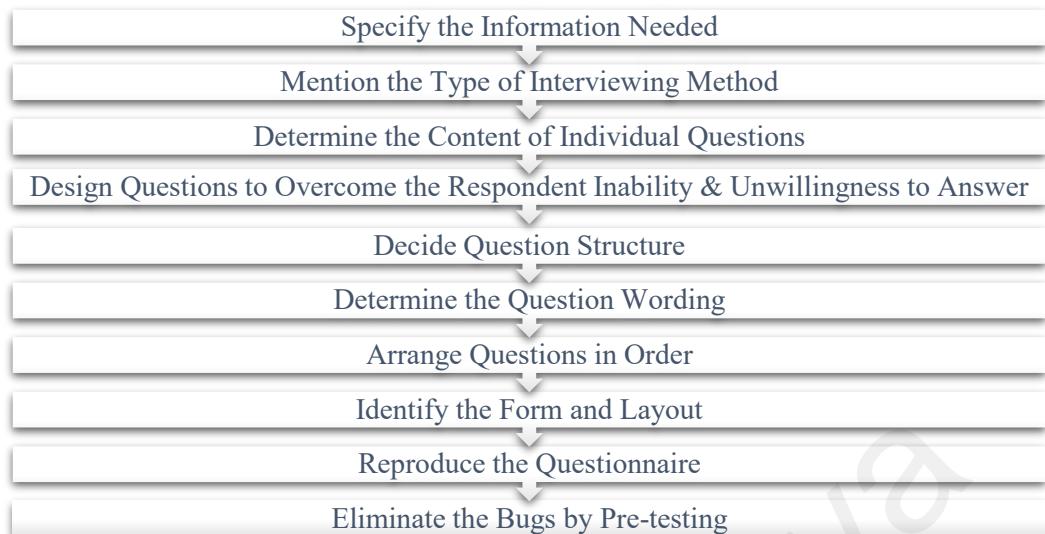


Figure 3.3: Questionnaire Design Process (Malhotra, 2010)

a. Specify the Information Needed

The first step of the questionnaire design process is to identify the information required. This information is derived from the research problem, research questions, and research hypotheses of this study. Moreover, considering the target population is important. The information required from each respondent was clearly described in the questionnaire (Appendix).

b. Mention the Type of Interviewing Method

The type of questionnaire is very important. It influenced the overall design of the questionnaire. This study employs a survey method. The main survey was conducted online. Thus, the designed questions were pertinent and straightforward. The complete instructions were provided at the start of the questionnaire for respondents.

c. Determine the Content of Individual Questions

This study is based on a theoretical model for big data adoption in VU campuses. Thus, the content of each question is written from technology, organization, and environment-based factors that can affect big data adoption in VU campuses. However, only relevant questions are considered for this study. The irrelevant demographic questions, such as salary, campus code, employee name, and telephone number were eliminated. The content of every question is designed to get specific purposes and extract relevant information for the study. The double-barreled and ambiguous questions are avoided.

d. Design Questions to Overcome the Respondent's Inability & Unwillingness to Answer

The questions were designed in a manner to overcome the inability and unwillingness to answer. The questions were framed in such a way that minimized the respondent's effort to answer. For each question, the definition was provided for the respondent's convenience. All the sensitive, personal, complicated, and imposing types of questions were avoided. The 'optional' is mentioned with questions to sustain the respondent's privacy. The proper information and legitimate purpose were provided. It was clearly described that respondent-provided information would only be used for statistical analysis purposes for this study. Any information collected will not be disclosed to third parties. To achieve the respondent's willingness, the respondent's reputation-related aspects were also considered. The overblown phrasing, and difficult, and uncommon words were avoided to support the respondent's ability.

e. *Decide Question Structure*

This study used the design of a structured question. It specifies the set of response options and the proper response arrangement. A structured question can be multiple choices, dichotomous, or a scale. In this study, the majority of the questions were scale-type. However, few demographic questions were dichotomous. For instance, the questionnaire contains questions like

Are you familiar with big data technologies?

- Yes
- No

Furthermore, items of the questionnaire were measured using a 5-point Likert scale. The 5 indicate strong agreement and 1 for strong disagreement. The Likert scale does not force respondents to express their opinion (Williams, 2007). Thus, it's easy for respondents to complete the structured questions as compared to unstructured questions. The format of the statement criteria is given in Figure 3.4.

Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Figure 3.4: Format of Statement Criteria

f. Determine the Question Wording

The questions worded were simple, clear, and easily understandable for respondents. The question's wording decreases the non-response error. The wording of the questions was specific and clearly described the study context. The positive and negative statements were used to avoid the biasing questions. ‘What’, ‘where’, ‘how’, and ‘when’ type words were avoided to reduce the ambiguity.

g. Arrange Questions in Order

The opening question starts with the respondent qualifying question. It verifies whether the respondent is eligible to take part in the survey. After that part, the demographic questions were started. These questions were simple and attracted the respondent's attention. All questions were logically arranged. The core questions began with technology, then subsequently organization and the environment.

h. Identify the Form and Layout

The questionnaire format and session spacing affect the response rate. The proper session spacing increases the response rate. Therefore, the questionnaire was divided into different sessions. For the demographic part, different sessions were created. Respondent role-related questions were put in a separate session. Question

overload per session is avoided to increase clarity. The questions in each session were easy to read. A session name is given to each session.

i. *Reproduce the Questionnaire*

It refers to “how a questionnaire is reproduced can influence the response rate”. Therefore, for this study, high-quality Double ‘A’ quality papers were used to print the questionnaire. The pages were arranged correctly and put in a separate envelope of paper. Directions and instructions were provided on the opening page of the questionnaire. The thanking note was given at the start and end of the questionnaire. All the supportive material was given before the start of the question.

j. *Eliminate the Bugs by Pre-testing*

In order to eliminate the bugs and pre-testing, the pilot study is conducted. The sample size of the pilot study varies from 10 to 30 respondents.

3.6.2 Measurement of Items

The questionnaire’s core content was based on technological, organizational, and environmental factors that affect big data adoption. The scale measurement of each item was adapted from existing research. The Likert scale was found to be more convenient for survey respondents. Therefore, a 5-point Likert scale was used to evaluate all factors. The ‘1’ is for strongly disagree and ‘5’ is for strongly agree.

a. Relative Advantages

The relative advantage is selected as it is the significant factor that can affect big data adoption. The relative advantage items and their references are presented in Table 3.1.

Table 3.1: Relative Advantage Items

	Items	References
	<ol style="list-style-type: none">1. Big data adoption enables to accomplish tasks more quickly2. Big data adoption gives greater control over work3. Big data adoption would enhance the data storage4. Big data adoption would be advantageous in the overall organization	Alshamaileh (2013); Tehrani (2013)

b. Complexity

The complexity factors are considered for this survey as it is an important aspect of innovation that can affect big data adoption. The complexity items and their references are presented in Table 3.2.

Table 3.2: Complexity Items

	Items	References
	<ul style="list-style-type: none"> 1. Big data technology is complicated to operate 2. Big data technology is difficult to understand and interact with 3. Big data technology takes too long to understand 4. Big data technology is not easy to implement 	Tehrani (2013)

c. *Compatibility*

Compatibility is a very important innovational factor that can affect big data adoption. The compatibility items and their references are presented in Table 3.3.

Table 3.3: Compatibility Items

	Items	References
	<ul style="list-style-type: none"> 1. Big data technology easily be integrated into existing infrastructure 2. Big data technology fits well for working style 3. Big data technology is well-matched with norms and tradition 4. Big data technology is well-suited with present data 	Tehrani (2013)

d. *IT Infrastructure*

The conceptualization of IT infrastructure is adapted from Tehrani (2013). The IT infrastructure is considered for this survey as it is an important organizational factor that can affect big data adoption. The IT infrastructure items, and its references are presented in Table 3.4.

Table 3.4: IT infrastructure Items

	Items	References
	<ol style="list-style-type: none"> 1. IT systems are capable for big data adoption 2. Present networks are robust for big data adoption 3. Available IT systems are capable to incorporate new changes for big data adoption 4. Overall, IT infrastructure is fit for big data adoption 	Tehrani (2013)

e. *Top Management Support*

The measures of top management support items were adapted from Premkumar and Roberts (1999). The top management support items and their references are presented in Table 3.5.

Table 3.5: Top Management Support Items

	Items	References
	<ol style="list-style-type: none"> 1. Top management believe that investment in big data adoption will worthwhile 2. Top management believes that big data adoption has the potential to enhance academic quality 3. Top management support is essential to provide the resources for big data adoption 4. Top management positively supports in overall big data adoption decision 	Premkumar and Roberts (1999)

f. *Financial Resources*

Financial resources are measured through four items. These items were adapted from Tehrani (2013) and Boonsiritomachai (2014). However, various studies were analyzed, but only the most relevant items were considered to measure the financial

aspects for big data adoption in virtual universities. The financial resources items and their references are presented in Table 3.6.

Table 3.6: Financial Resource Items

Items	References
<ol style="list-style-type: none"> 1. University have financial resources for big data adoption 2. University has no troubles in finding all the needed resources for big data adoption 3. University has financial resources to enhance the infrastructure for big data adoption 4. University have financial resources to hire experts for big data adoption 	Tehrani (2013); Boonsiritomachai (2014)

g. Human Expertise and Skills

The framing of items was adapted from Ravichandran and Lertwongsatien (2005) and Boonsiritomachai (2014). Human expertise is selected as it is essential and plays a significant role in big data adoption. It smooths the overall big data adoption process. The items and its references are shown in Table 3.7.

Table 3.7: Human Expertise and Skills Items

Items	References
<ol style="list-style-type: none"> 1. IT employees have sufficient technical knowledge to implement big data technology 2. IT employees have the ability to rapidly learn and adopt innovation 3. Employees have the proficiency and information to maintain big data technologies 4. University has strong programmers and database managers for big data adoption 	Ravichandran and Lertwongsatien (2005); Boonsiritomachai (2014)

h. Competitive Pressure

The competitive pressure items were adapted from Premkumar and Roberts (1999).

The selected items were relevant to construct to assess the significance in the

adoption context. The competitive pressure items and their references are shown in Table 3.8.

Table 3.8: Competitive Pressure Items

	Items	References
	<ol style="list-style-type: none"> 1. Institute would lose reputation if did not adopt big data 2. Big data adoption is a necessity to compete with the other universities 3. Other universities get advantages through big data adoption 4. Other universities are going to adopt big data in the near future 	Premkumar and Roberts (1999)

i. *Security and Privacy Concerns*

The instrument was measured through four items. The items were adapted from Khater (2017). The security and privacy items and their references are presented in Table 3.9.

Table 3.9: Security and Privacy Concerns Items

	Items	References
	<ol style="list-style-type: none"> 1. Big data adoption is not secure enough to store academic data 2. Taking a risk to adopt big data is disadvantageous than the benefits 3. Security and privacy concerns affect big data adoption decision 4. Personal information may be exposed to other parties after big data adoption 	Khater (2017)

j. *Government Policies*

The government policy items, and their references are presented in Table 3.10.

Table 3.10: Government Policies Items

	Items	References
1.	Government policies give confidence and relaxation to adopt big data	Ochieng (2015)
2.	Government policies encourage the provision of access to the internet on all campuses	
3.	Government policies encourage digitization of services that enable an environment for big data adoption	
4.	University follows government policies to implement new technology	

k. *University Age*

The items and their references are presented in Table 3.11.

Table 3.11: University Age Items

	Items	References
1.	Older institutes have more experience to handle big data adoption	Ochieng (2015)
2.	Older institutions easily accept technical transformation big data adoption	
3.	Older institutions have more IT resources for big data adoption	
4.	Older institutions lack willingness to adopt big data	

l. *University Size*

The items and their references are presented in Table 3.12.

Table 3.12: University Size Items

	Items	References
1.	Number of employees enhance institutional capability for big data adoption	Ochieng (2015); Khater (2017)
2.	Number of employee's effect on skills and expertise to adopt big data	
3.	Number of employees enhance overall efficiency to adopt big data	
4.	Number of the employee is a significant indicator for big data adoption decision	

m. Big Data Adoption

This study used four items to measure the instrument. These items were adapted from (Premkumar and Roberts, 1999; Khater, 2017). The big data adoption items and their references are presented in Table 3.13.

Table 3.13: Big data adoption Items

	Items	References
	<ol style="list-style-type: none">1. University intent to adopt big data technology2. University will adopt big data technologies within 5 years3. I confidently recommend big data technology to university4. In the future study, I would use big data technologies confidently in university	Premkumar and Roberts (1999); Khater (2017)

3.6.3 Content Validity

Content validity is the degree to which study items are presented to determine their relevance to a particular realm (Polit & Beck, 2006). The expert opinion ascertains whether the designed item is relevant to study and simple to understand (Yaghmaei, 2003). Content validity is a vital step in instrument development. Neither statistical analysis nor other strategies are a replacement for content validity. The content validity is usually assessed by 3 to 4 experts (Polit, Beck, & Owen, 2007).

Content validity was used to ascertain the simplicity and relevancy of a designed instrument. In this study, the content validity of the questionnaire was accomplished by experts in this field. The content of the questionnaire was revised

further in the light of experts' suggestions. The whole process was completed in 6 months. All experts were selected based on their expertise.

A draft of questionnaire items was sent to experts. The proposed theoretical model and hypotheses were also enclosed with a questionnaire to get a comprehensible view of the relevancy of items with constructs. Five experts reviewed the questionnaire and gave their opinion. The three experts came from academic backgrounds; one was a professional big data consultant, and the other had previously worked as a consultant in an analytic data company. The expert's professional and experience details are provided in Table 3.14.

Table 3.14: Expert Profile

Experts	Professions	Experience
Expert 1	Academician	A professor in a government institution. Serving for the last 25 years in the academic field. Experts in statistics, quantitative and qualitative data analysis.
Expert 2	Academician and Consultant	Assistant professor in a university. Serving for the last 10 years in the academic field. Before joining the academic field worked as a consultant in a data analytic company. Experts in statistics, research methods, quantitative, and qualitative data analysis.
Expert 3	Professional consultant	A master's in science working as a senior consultant in a big data analytics company. Diverse experience in data science and artificial intelligence. Offering big data services in Pakistan and America.
Expert 4	Academician	A PhD working as an assistant professor in a computer science department. Serving in the academic's field from the last 10 years. Currently, teaching data science and big data courses to postgraduate students.
Expert 5	Academician	A PhD degree working as an assistant professor in an Institution. 11 years of teaching experience. Expert in big data and Structured Query Language.

The content validity for each item is the percentage of expert responses that rated the item as 1 to 4. Experts were asked to review the draft and evaluate each item based on two criteria, namely relevance and simplicity. The experts were also asked to suggest revisions to item if needed. Each reviewer independently rated on Lynn (1996) 4-point scale (1=not relevant, 2=somewhat relevant, 3=relevant, 4=very relevant), and (1=not simple, 2=somewhat simple, 3=simple, 4=very simple). The rating scale for expert opinion is presented in Table 3.15. The content validity index is calculated in the form of a percentage. The value of 1.00 is acceptable for 3 to 4 expert's panels (Yaghmaei, 2003). The 0.78 is acceptable for 5 experts' panels (Polit and Beck, 2006). The content validity index gauges the content validity of individual items. Content validity index (I-CVI) is the most used method to calculate Item-level validity. For instance, 4 out of 5 experts agree on an item, then I-CVI is $4/5 = 0.80$.

However, S-CVI calculates the content validity of the overall scale. S-CVI can be calculated by using S-CVI/UA, Universal Agreement (UA) or S-CVI/Ave (Polit and Beck, 2006). Most of the studies reported only I-CVI or S-CVI (Rodrigues, Adachi, Beattie, & MacDermid, 2017). However, this study employed all methods. S-CVI/UA (Universal Agreement (UA) is calculated by adding all items with I-CVI equal to 1 divided by the total number of items. However, S-CVI/Ave is calculated by taking the sum of the I-CVIs divided by the total number of items. The S-CVI/UA should be greater than equal to 0.8. However, S-CVI/Ave should be greater than equal 0.9 (Rodrigues et al., 2017). The S-CVI/UA values in terms of simplicity and reliability were greater than 0.8. Similarly, S-CVI/Ave values in terms of simplicity and reliability were greater than 0.9. The complete results of 1-CVI, S-CVI/UA, and S-CVI/Ave are shown in Table 3.16 and Table 3.17.

Table 3.15: Rating Scale for Expert Opinion

Scores	1	2	3	4
Relevance	Not relevant	Item need revision	Relevant but needs minor revision	Very relevant
Simplicity	Not simple	Item need revision	Simple but needs minor revision	Very simple

Table 3.16: Expert's Opinion in Terms of Simplicity of Items

No of Items	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Number of Agreement	I-CVI
1	4	3	4	4	3	5	1
2	4	4	3	4	3	5	1
3	4	3	4	4	4	5	1
4	3	3	3	4	3	5	1
5	4	3	4	4	4	5	1
6	4	4	4	4	4	5	1
7	3	4	4	3	3	5	1
8	4	4	4	4	3	5	1
9	3	3	3	4	4	5	1
10	4	4	4	4	4	5	1
11	4	4	4	4	4	5	1
12	4	3	4	4	4	5	1
13	4	4	4	4	4	5	1
14	4	3	4	4	4	5	1
15	3	3	3	3	3	5	1
16	4	4	4	4	4	5	1
17	4	4	4	4	4	5	1
18	2	4	4	4	4	4	0.8
19	3	3	2	4	4	4	0.8
20	4	4	4	3	4	5	1
21	4	4	4	4	4	5	1
22	4	4	3	4	4	5	1
23	4	4	4	4	4	5	1
24	3	1	4	4	4	4	0.8
25	3	3	4	3	3	5	1
26	4	4	3	3	4	5	1
27	4	4	4	4	4	5	1
28	3	3	2	4	4	4	0.8
29	4	4	4	4	4	5	1
30	4	1	4	4	3	4	0.8
31	4	4	4	4	4	5	1
32	4	4	4	4	4	5	1
33	4	4	4	3	3	5	1
34	4	4	4	4	4	5	1
35	4	3	4	4	4	5	1
36	4	4	4	4	4	5	1
37	4	4	3	4	4	5	1
38	4	4	4	4	4	5	1
39	4	4	4	4	3	5	1
40	4	4	4	3	4	5	1

Table 3.16: Expert's Opinion in Terms of Simplicity of Items (Con't)

No of Items	Expert 1	Expert2	Expert3	Expert4	Expert5	Number of Agreement	I-CVI
41	4	4	4	4	4	5	1
42	4	4	4	4	3	5	1
43	4	3	4	4	4	5	1
44	4	4	4	4	4	5	1
45	4	4	3	4	3	5	1
46	4	4	4	4	4	5	1
47	4	4	4	4	4	5	1
48	3	3	3	4	4	5	1
49	3	4	3	4	4	5	1
50	4	4	4	4	4	5	1
51	3	3	3	3	3	5	1
52	4	3	4	4	4	5	1
						S-CVI/Ave	0.980769
						Total Agreement	47
						S-CVI/UA	0.9

Table 3.17: Experts Opinion in Terms of Relevancy of Items

No of Items	Expert1	Expert2	Expert3	Expert4	Expert5	Number of Agreement	I-CVI
1	4	4	4	4	4	5	1
2	4	4	4	4	4	5	1
3	4	4	4	4	4	5	1
4	3	4	4	4	3	5	1
5	4	3	4	4	4	5	1
6	4	4	4	4	4	5	1
7	3	4	4	3	3	5	1
8	4	4	4	4	3	5	1
9	3	3	3	4	4	5	1
10	4	4	4	4	4	5	1
11	4	4	4	4	4	5	1
12	4	4	4	4	4	5	1
13	4	4	4	4	4	5	1
14	4	4	4	4	4	5	1
15	3	3	3	3	2	4	0.8
16	4	4	4	4	4	5	1
17	4	4	4	4	4	5	1
18	1	4	4	4	4	4	0.8
19	3	3	4	4	4	5	1
20	4	4	4	4	4	5	1
21	4	4	4	4	4	5	1
22	4	4	4	4	4	5	1
23	4	4	4	4	4	5	1
24	3	2	4	4	4	4	0.8
25	3	3	4	3	3	5	1
26	4	4	4	3	4	5	1
27	4	4	4	4	4	5	1
28	3	3	1	4	4	4	0.8
29	4	4	4	4	4	4	0.8
30	4	2	4	4	4	4	0.8
31	4	4	4	4	4	5	1
32	4	4	4	4	4	5	1
33	4	4	4	4	4	5	1
34	4	4	4	4	4	5	1
35	4	4	4	4	4	5	1
36	4	4	4	4	4	5	1
37	4	4	4	4	4	5	1
38	4	4	4	4	4	5	1
39	4	4	4	4	4	5	1

Table 3. 17: Experts Opinion in Terms of Relevancy of Items (Con't)

No of Items	Expert1	Expert2	Expert3	Expert4	Expert5	Number of Agreement	I-CVI
40	4	4	4	3	4	5	1
41	4	4	4	4	4	5	1
42	4	4	4	4	4	5	1
43	4	4	4	4	4	5	1
44	4	4	4	4	4	5	1
45	4	4	3	4	3	5	1
46	4	4	4	4	4	5	1
47	4	4	4	4	4	5	1
48	3	3	3	4	4	5	1
49	3	4	3	4	4	5	1
50	4	4	4	4	4	5	1
51	3	3	3	3	3	5	1
52	4	4	4	4	4	5	1
						S-CVI/Ave	0.9769
						Total Agreement	46
						S-CVI/UA	0.88

3.7 Data Analysis Methods

In this study, statistical procedures are employed to check the validity of the proposed big data adoption model. This helps to identify the significant factors that influence big data adoption in the higher education sector. The analysis consisted of two parts. The first data analysis section is for descriptive data. Excel 2007 is used to analyze the respondent profile data. The second section is based on the validation of the model. The PLS-SEM is used through the SmartPLS 3.2.8 tool to test the validation. Multiple analyses were performed to test the model.

3.7.1 Descriptive Data

Descriptive data is basically based on the sample characteristics. In this study, descriptive data is based on respondents' profiles, namely: gender, age, role, and experience. However, the respondent profiles are collected from IT management-related managers from VU campuses. It is reported using frequency and percentages.

3.7.2 Partial Least Squares Structural Equation Modelling

Partial Least Squares Structural Equation Modelling (PLS-SEM) is a second-generation statistical technique used to analyze complex models with multiple associations, incorporating both latent and observed variables (Hair, Hult, Ringle, & Sarstedt, 2017). PLS-SEM is turning into a well-known statistical framework in numerous fields. PLS-SEM can be used to assess models including latent variables, observed variables, or a blend of these. The notoriety of PLS-SEM is anticipated to increment considerably more because of the advancement of new and more robust assessments. The customary assessment strategies for PLS-SEM are currently

being promptly encouraged by both open-source and business programming bundles.

PLS-SEM empowers analysts to demonstrate and assess complex reason impact relationship models with both latent and observed variables. The latent variables encapsulate unseen (i.e., not straightforwardly quantifiable) marvels like insights, mentalities, and expectations. The observed variables (e.g., reactions to a poll or questionnaire) are utilized to address the latent variables in a measurable model. PLS-SEM gauges the connections between the latent variables (i.e., their qualities) and decides how well the model clarifies the objective builds of interest. PLS-SEM is a robust method used for evaluation and theory prediction, especially in big data and technology adoption research (Hair Sarstedt, Hopkins & Kuppelwieser, 2014). PLS explains the path model through the structural model and measurement model (Henseler, Hubona, & Ray, 2016). The structural model uncovers the relationships between the constructs. However, measurement models expose the relationships between the constructs and item variables (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017).

The aim of this study is to assess whether the factors suggested through the proposed model are effective in predicting the adoption of big data in the higher education sector. Therefore, the goal of this research is to determine the predictive validity of independent variables. This predictive validity explicates the relationship of technology, organization and environment-related constructs with the adoption of big data in VU. This research used the PLS-SEM modelling technique to predict and clarify the relationship between determinants and the adoption of big data in higher education. SmartPLS consolidates cutting-edge

techniques in variable modelling. Therefore, SmartPLS 3.0 series was employed to perform the analysis.

3.7.3 Structural Model Analysis

To conduct the analysis, the Teddlie & Tashakkori (2006) PLS-SEM technique was applied, which is profoundly a pivot method in the statistical modelling technique (Hair et al., 2021). The PLS-SEM consists of two analyses. The first is a measurement model (outer-model), which is used to ascertain the relationship that exists among items and their related constructs (Hair et al., 2016). The second is the structural model (inner-model), used to uncover the association between the constructs of the model (Sarstedt, Ringle, Smith, Reams, & Hair, 2014).

- Measurement Model (Outer-Model) Assessment

To assess the reliability and validity of constructs, different tests are required to be performed. Construct reliability is the degree that determines how reliable the construct is or can be quantified in prediction (Ringle & Sarstedt, 2016). In contrast, construct validity is the degree to which a test determines what it states. In PLS, construct validity examines how an item performs with other indicators (Sarstedt et al., 2017).

- a. *Construct Reliability*

Construct reliability was analyzed through indicator reliability and internal consistency. It was tested through the PLS algorithm option given SamrtPLS 3. The indicator reliability was analyzed by factor loadings. However, construct reliability was tested by calculating Cronbach's alpha and composite reliability. According to Sinkovics, Henseler, Ringle, & Sarstedt (2016), factor loadings, Cronbach's alpha, and composite reliability values greater than 0.7 were acceptable.

b. Construct Validity

Construct validity was analyzed with convergent validity and discriminant validity.

Convergent validity is the degree of measures that are supposed to be used in measuring the same construct (Hair et al., 2017). Discriminant validity indicates the degree to which a construct is different from other constructs (Ringle & Sarstedt, 2016).

Convergent validity was assessed with the average variance extracted (AVE). The recommended value of AVE is equal to or greater than 0.5 (Hair et al., 2016).

Discriminant validity was assessed with the Fornell-Larcker criterion (Rigdon, Sarstedt, & Ringle, 2017), cross-loading criterion and heterotrait-monotrait ratio (Henseler et al., 2016). In the Fornell-Larcker criterion, the square root of AVE should be greater than any of the co-related construct correlations (Hair et al., 2021). In cross-loadings, the factor loading of all construct items values was greater than other loadings in terms of row and column. Heterotrait-monotrait values less than the threshold of 0.90 are acceptable (Streukens, & Leroi-Werelds, 2016; AbHamid, Sami, & Sidek, 2017).

■ Structural Model (Inner-Model) Assessment

Structural model measurement was carried out after an assessment of the outer model. The bootstrapping process was performed to test the hypothesis that is based on the direct and moderating effects. Bootstrapping is basically a procedure to identify the path coefficients and thus the status of hypotheses (acceptance or rejection). It has a built-in option for examining the direct and indirect effects. In bootstrapping, subsamples are created with randomly drawn observations from the

original set of data (with replacement). The subsample is then used to estimate the PLS path model.

This process is repeated until a large number of random subsamples have been created, typically about 5,000. In the inner model, measurement values of path coefficient, t-values, and p-values were analyzed.

a. *R² Assessing Model Integrity*

R² is used to evaluate the integrity of the model (Rigdon, Sarstedt, & Ringle, 2017; Hair et al., 2021). It explains the variance and predictive power (Sarstedt, Ringle, & Hair, 2017). According to Cohen (1992), R² value of (0.26) is considered substantial, (0.13) moderate, and (0.02) considered weak.

3.8 Pilot Study

A pilot study was conducted to test the preliminary reliability and validity of the developed questionnaire before the start of the main study. Statistical power increases with sample size (Hair et al., 2021). Small samples of 30 to 40 participants are common in the preliminary testing of questionnaires. However, small may fail to expose problems and analyze the small-scale data precisely (Arain, 2010). A default sample size of 80 to 100 participants is mostly recommended for the pilot study (Hertzog, 2008). The reliability and validity of the questionnaire were also tested through a pilot study with 87 IT-related staff of VU campuses before conducting the main study. The pilot study took two months. The questionnaire was created through google form and a link was emailed to the managerial side of VU. Besides, respondents had to be reminded to reply to the questionnaire every week.

The major objective of conducting the study was to test the reliability and validity of questionnaires within the context of this study. Therefore, data were collected from the managerial side, and statistical analysis was conducted. The SEM is used to analyze the reliability and validity of questionnaires. The reliability of the questionnaire was tested through actor loadings, Cronbach alpha, and composite reliability. However, the validity of the questionnaire was tested through convergent validity and discriminant validity. The convergent validity was ascertained through the average variance extracted. Nevertheless, the discriminant validity was assessed through the Fornell-Larcker criterion and cross-loading. According to Hair et al. (2017), factor loading, and Cronbach alpha value should be greater than 0.7. It was found that the factor of one item of complexity was less than 0.7. Therefore, the item of complexity (complex 1) needs to be removed as its Cronbach's alpha was 0.66 and its factor loaded value was 0.28.

The pilot study results of the factor loading, reliability, and convergent validity are presented in Table 3.18. After removing the complexity (complex 1) the test was performed again. Finally, it was found that factor loadings, Cronbach alpha and composite reliability of all items were greater ($>$) than 0.7. The validity of the questionnaire was assessed through convergent and discriminant validity. The convergent validity was assessed through average variance extracted and discriminant validity through cross-loadings and the Fornell-Larcker Criterion (the detail of acceptance criteria is presented in Section 3.7.3). The average variance extracted values were greater than 0.5. The cross-loading items are high-loadings. The square root of each average factor variance extracted was higher than its correlation with another factor.

The pilot study results of Cross Loading are presented in Table 3.19. However, the pilot study results Fornell-Larcker Criterion s presented in Table 3.20. All the results confirmed the validity of the questionnaire.

Table 3.18: Results of Questionnaire (Pilot Study)

Constructs	Item	Factor Loading (>0.7)	Reliability		Convergent Validity AVE (>0.5)
			Cronbach's Alpha (>0.7)	Composite Reliability (>0.7)	
Big data adoption (BDA)	BDA1	0.78	0.81	0.87	0.63
	BDA2	0.80			
	BDA3	0.79			
	BDA4	0.81			
Relative Advantage (RA)	RA1	0.83	0.79	0.87	0.60
	RA2	0.81			
	RA3	0.83			
	RA4	0.71			
Complexity (Complex)	Complex	0.80	0.74	0.85	0.66
	Complex	0.82			
	Complex	0.81			
Compatibility (Compat)	Compat1	0.87	0.85	0.90	0.70
	Compat2	0.85			
	Compat3	0.80			
	Compat4	0.81			
IT infrastructure (ITinf)	ITinf1	0.71	0.75	0.84	0.57
	ITinf2	0.78			
	ITinf3	0.71			
	ITinf4	0.83			
Top Management Support (TMS)	TMS1	0.86	0.87	0.91	0.73
	TMS2	0.88			
	TMS3	0.80			
	TMS4	0.87			

Table 3.18: Results of Questionnaire (Pilot Study) (Con't)

Constructs	Item	Factor Loading (>0.7)	Reliability		Convergent Validity AVE (>0.5)
			Cronbach's Alpha (>0.7)	Composite Reliability (>0.7)	
Financial Resource (FR)	FR1	0.85	0.84	0.90	0.72
	FR2	0.83			
	FR3	0.81			
	FR4	0.89			
Competitive Pressure (CP)	CP1	0.86	0.86	0.91	0.71
	CP2	0.87			
	CP3	0.76			
	CP4	0.87			
Human expertise and skills (HE)	HE1	0.86	0.85	0.91	0.69
	HE2	0.87			
	HE3	0.77			
	HE4	0.81			
Security & Privacy (SP)	SP1	0.78	0.83	0.89	0.66
	SP2	0.89			
	SP3	0.73			
	SP4	0.84			
Government policies (GP)	GP1	0.73	0.76	0.85	0.58
	GP2	0.82			
	GP3	0.76			
	GP4	0.74			
University Age (UA)	UA1	0.90	0.89	0.93	0.76
	UA2	0.87			
	UA3	0.85			
	UA4	0.87			
University Size (US)	US1	0.84	0.81	0.88	0.64
	US2	0.77			
	US3	0.76			
	US4	0.82			

Table 3.19: Pilot Study Results of Cross Loading

	BDA	CP	Compat	Complex	FR	GP	HR	IT inf	RA	SP	TMS	UA	US
BDA1	0.78	0.75	0.57	0.48	0.69	0.61	0.77	0.63	0.69	0.67	0.64	0.62	0.71
BDA2	0.80	0.62	0.61	0.50	0.58	0.64	0.60	0.65	0.58	0.65	0.70	0.55	0.59
BDA3	0.79	0.47	0.69	0.56	0.47	0.63	0.48	0.61	0.60	0.51	0.50	0.40	0.60
BDA4	0.81	0.57	0.68	0.57	0.53	0.62	0.46	0.64	0.64	0.56	0.56	0.51	0.58
CP1	0.65	0.86	0.51	0.47	0.70	0.62	0.78	0.67	0.66	0.65	0.66	0.60	0.76
CP2	0.61	0.87	0.57	0.52	0.71	0.61	0.77	0.56	0.67	0.62	0.58	0.65	0.73
CP3	0.62	0.76	0.67	0.71	0.62	0.68	0.57	0.63	0.64	0.59	0.62	0.56	0.65
CP4	0.70	0.87	0.56	0.50	0.68	0.59	0.78	0.59	0.76	0.69	0.68	0.68	0.76
Compat1	0.75	0.59	0.87	0.62	0.60	0.60	0.52	0.67	0.68	0.60	0.57	0.53	0.64
Compat2	0.66	0.57	0.85	0.74	0.54	0.65	0.51	0.64	0.65	0.51	0.54	0.50	0.65
Compat3	0.62	0.63	0.80	0.70	0.63	0.61	0.64	0.62	0.65	0.62	0.61	0.55	0.67
Compat4	0.62	0.50	0.81	0.58	0.52	0.67	0.51	0.59	0.60	0.51	0.56	0.46	0.50
Complex2	0.56	0.63	0.59	0.80	0.65	0.64	0.55	0.56	0.68	0.61	0.59	0.55	0.63
Complex3	0.51	0.44	0.67	0.82	0.46	0.65	0.38	0.48	0.47	0.41	0.40	0.32	0.47
Complex4	0.54	0.51	0.66	0.81	0.46	0.70	0.49	0.58	0.60	0.48	0.53	0.43	0.55
FR1	0.65	0.54	0.55	0.59	0.85	0.62	0.72	0.61	0.65	0.56	0.64	0.64	0.75
FR2	0.57	0.58	0.59	0.53	0.83	0.61	0.75	0.58	0.62	0.50	0.62	0.65	0.63
FR3	0.70	0.69	0.62	0.50	0.81	0.60	0.70	0.66	0.63	0.57	0.64	0.62	0.66
FR4	0.61	0.64	0.57	0.58	0.89	0.63	0.75	0.60	0.69	0.54	0.66	0.69	0.68
GP1	0.65	0.70	0.57	0.55	0.73	0.73	0.82	0.65	0.62	0.53	0.67	0.63	0.75
GP2	0.68	0.58	0.68	0.62	0.61	0.82	0.55	0.67	0.60	0.65	0.62	0.53	0.67
GP3	0.52	0.44	0.67	0.68	0.40	0.76	0.35	0.58	0.48	0.41	0.38	0.33	0.50
GP4	0.51	0.42	0.72	0.67	0.42	0.74	0.43	0.54	0.53	0.38	0.38	0.36	0.43
HR1	0.59	0.73	0.57	0.53	0.68	0.61	0.86	0.58	0.60	0.61	0.65	0.65	0.73
HR2	0.72	0.62	0.57	0.51	0.72	0.67	0.87	0.61	0.63	0.63	0.63	0.67	0.73
HR3	0.51	0.70	0.52	0.49	0.70	0.58	0.77	0.47	0.66	0.60	0.65	0.69	0.66
HR4	0.61	0.65	0.50	0.43	0.76	0.55	0.81	0.58	0.66	0.62	0.66	0.64	0.63
ITinf1	0.53	0.39	0.47	0.29	0.42	0.44	0.38	0.71	0.45	0.47	0.42	0.45	0.46
ITinf2	0.64	0.55	0.70	0.67	0.61	0.72	0.53	0.78	0.59	0.58	0.58	0.52	0.57
IT inf3	0.47	0.46	0.42	0.40	0.46	0.48	0.37	0.71	0.42	0.49	0.42	0.39	0.46
ITinf4	0.76	0.61	0.65	0.60	0.66	0.73	0.69	0.83	0.69	0.68	0.64	0.62	0.71
RA1	0.67	0.69	0.59	0.58	0.76	0.64	0.82	0.65	0.83	0.60	0.60	0.69	0.72
RA2	0.66	0.63	0.54	0.53	0.69	0.57	0.70	0.51	0.81	0.72	0.69	0.74	0.70
RA3	0.67	0.68	0.67	0.60	0.73	0.64	0.70	0.62	0.83	0.61	0.72	0.68	0.70
RA4	0.53	0.41	0.69	0.67	0.39	0.62	0.35	0.55	0.71	0.39	0.35	0.30	0.43
SP1	0.58	0.57	0.55	0.47	0.71	0.58	0.72	0.54	0.69	0.78	0.72	0.70	0.69
SP2	0.68	0.65	0.56	0.47	0.72	0.61	0.77	0.63	0.74	0.89	0.81	0.71	0.75

Table 3.19: Pilot Study Results of Cross Loading (Con't)

SP3	0.69	0.56	0.58	0.51	0.59	0.59	0.52	0.69	0.61	0.73	0.59	0.51	0.58
SP4	0.61	0.70	0.49	0.56	0.75	0.59	0.74	0.56	0.68	0.84	0.75	0.70	0.70
TMS1	0.62	0.66	0.51	0.46	0.76	0.53	0.74	0.57	0.64	0.53	0.86	0.76	0.68
TMS2	0.74	0.68	0.61	0.52	0.63	0.67	0.65	0.61	0.60	0.50	0.88	0.61	0.64
TMS3	0.62	0.52	0.57	0.49	0.74	0.58	0.80	0.62	0.61	0.61	0.80	0.69	0.71
TMS4	0.70	0.75	0.62	0.65	0.74	0.68	0.78	0.60	0.74	0.68	0.87	0.69	0.65
UA1	0.63	0.72	0.52	0.45	0.76	0.58	0.79	0.60	0.68	0.64	0.78	0.90	0.66
UA2	0.65	0.74	0.55	0.44	0.74	0.55	0.78	0.58	0.72	0.63	0.74	0.87	0.60
UA3	0.63	0.74	0.54	0.47	0.78	0.57	0.74	0.55	0.68	0.62	0.69	0.85	0.63
UA4	0.64	0.81	0.53	0.51	0.80	0.61	0.79	0.60	0.75	0.57	0.78	0.87	0.72
US1	0.70	0.68	0.55	0.48	0.68	0.63	0.75	0.63	0.67	0.65	0.76	0.68	0.84
US2	0.65	0.70	0.67	0.59	0.59	0.68	0.59	0.68	0.66	0.64	0.60	0.53	0.77
US3	0.58	0.70	0.60	0.57	0.64	0.58	0.62	0.52	0.60	0.62	0.59	0.61	0.76
US4	0.58	0.69	0.56	0.54	0.67	0.63	0.69	0.56	0.68	0.67	0.67	0.68	0.82

(RA= relative advantage, BDA = big data adoption, Complex = complexity, Compat = compatibility, IT inf = IT Infrastructure, TMS = top management support, FR = financial resources, HE = human expertise and skills, CP = competitive advantage, SP = security and privacy concerns, GP = government policies, US = university size, UA= university age)

Table 3.20: Pilot Study Results Fornell-Larcker Criterion

	BDA	GP	Complex	Compat	ITinf	TMS	FR	HE	CP	SP	RA	US	UA
BDA	0.90												
GP	0.61	0.92											
Complex	0.72	0.61	0.91										
Compat	0.71	0.58	0.73	0.96									
ITinf	0.67	0.53	0.71	0.68	0.92								
TMS	0.68	0.57	0.68	0.58	0.68	0.94							
FR	0.73	0.66	0.78	0.70	0.78	0.76	0.93						
HE	0.57	0.68	0.78	0.68	0.75	0.74	0.85	0.89					
CP	0.52	0.53	0.61	0.59	0.58	0.66	0.72	0.78	0.93				
SP	0.87	0.46	0.81	0.55	0.68	0.68	0.73	0.67	0.62	0.91			
RA	0.47	0.62	0.47	0.71	0.76	0.79	0.87	0.75	0.70	0.52	0.95		
US	0.54	0.38	0.58	0.43	0.52	0.69	0.61	0.66	0.72	0.61	0.62	0.89	
UA	0.58	0.49	0.63	0.62	0.63	0.70	0.75	0.84	0.86	0.70	0.70	0.71	0.93

Note: Bold diagonal elements represent the Average Variance Extracted (AVEs) for the relevant construct.

(RA= relative advantage, BDA = big data adoption, Complex = complexity, Compat = compatibility, IT inf = IT Infrastructure, TMS = top management support, FR = financial resources, HE = human expertise and skills, CP = competitive advantage, SP = security and privacy concerns, GP = government policies, US = university size, UA= university age)

3.9 Summary

This chapter presented the research design, research paradigms, and selected paradigms for this study. Additionally, the research design, sampling technique, participants, sample size, and data collection were presented. Moreover, instrument development was elaborated. The measurement of items was presented in detail. Moreover, the content validity is analyzed. Furthermore, data analysis tools and methods were described. Finally, a pilot study was conducted to ascertain the validity and reliability of the questionnaire. The next chapter describes the data analysis process in detail.

CHAPTER 4: MODEL AND HYPOTHESES DEVELOPMENT

4.1 Introduction

This chapter covers the model development process for this study. The first section describes the factors and research model development. This section is followed by the description of independent constructs and moderators for big data adoption. Furthermore, it describes the extracted factors through big data adoption studies. This section is followed by a subsection that covers the detailed justification of selected factors for this study. Finally, hypotheses development and a diagrammatic view of the proposed model are presented.

4.2 Identify Factors and Research Model Development

The identified factors and detail of research model development is presented below.

4.2.1 Independent Constructs and Moderators for Big Data Adoption Model

The independent constructs of this study are relative advantage, complexity, compatibility, IT infrastructure, top management support, financial resources, human expertise and skills, competitive pressure, security and privacy concerns. However, these independent constructs are categorized into technology, organization, and environment dimensions. The use of moderators is important to consider on key determinants for dynamic effects; therefore, it allows the enhancement of quality for adopting on the research models (Lai, Sun, & Ren, 2018). Age (years of existence) and Size (Total employees) can be helpful to test for the possibility of heterogeneity (Ochieng, 2015; Tashkandi & Al-Jabri, 2015; Akram, Tang, Tariq, 2020; KatzMS, 2022). Therefore, the age of the university and

the size of the university will be used to check the effect with other constructs. According to Table 2.4 (Chapter 2), the identified factors were also significantly used in different adoption contexts in the higher education sector. Therefore, the identified constructs were related to big data adoption and educational studies as well.

4.2.2 Technology Organization Environment and Diffusion of Innovation

Due to the swift advancement of information technology, the applicability of a single theoretical model is arguable (Lai et al., 2018). Therefore, it is imperative to adopt more than one model to get a comprehensive understanding of technology adoption. The TOE and DOI can better explain innovation from the organization perspective and observe the internal and external factors more effectively. TOE and DOI provide highly useful theoretical frameworks for big data adoption (Verma & Bhattacharyya, 2017). TOE framework prevails over the dominance of the technical side (Lai et al., 2018). DOI, on the other hand, provides a broad perception of the occurrence of diffusion and provides good explanations for how innovations can be adopted (Nguyen & Petersen, 2017). Simultaneously, DOI and TOE provide enhanced predictive power that can be used to detect and unravel technological and innovational adoption issues at an earlier stage (Verma & Bhattacharyya, 2017). DOI has been extensively used to promote the adoption of technology. However, TOE is considered for the prediction of technological, organization, and environmental factors. Hence, DOI and TOE promise a useful theoretical outcome to drive a new model for big data adoption (Baig et al., 2019). Thus, this research proposes a model based on the TOE and DOI framework as a theoretical base (Figure 4.1).

4.2.3 Extracted Factors through Big Data Adoption Studies

This study proposed a theoretical model by incorporating the DOI and TOE frameworks. The constructs were identified through big data adoption studies (Table 4.1). However, considering TOE and DOI as a base for model development, these constructs can be categorized as technology, organization, and environmental contexts according to the nature of these constructs (Figure 4.1). Moreover, to evade redundancy and obtain more comprehending results, some of the constructs were assembled together in the same group.

In total, ten constructs were extracted through big data adoption studies that match the scope of this study, namely: technology (relative advantage, complexity, compatibility, IT infrastructure), organization perceptive (top management support, financial resources, human expertise and skills) and environmental context (competitive pressure, security and privacy concerns and government policies).

Table 4.1: Extracted Constructs through Big Data Adoption Studies

Authors	Technology	Organization	Environment							
	Relative Advantage	Complexity	Compatibility	IT Infrastructure	Top management support	Financial resource	Human expertise & skills	Competitive pressure	Security & privacy concerns	Government policies
Yadegaridehkordi et al. (2020)	✓	✓	✓		✓	✓			✓	
Yadegaridehkordi et al. (2018)		✓			✓	✓	✓	✓		✓
Sun, Cegielski, Jia, & Hall (2018)	✓	✓	✓	✓	✓	✓	✓		✓	✓
Lai, Sun, & Ren (2018)		✓		✓	✓	✓				✓
Nguyen & Petersen (2017)	✓	✓	✓		✓		✓	✓	✓	
Verma & Bhattacharyya (2017)		✓	✓		✓	✓		✓		
Almoqren & Altayar (2016)				✓	✓		✓	✓		
Salleh & Janczewski (2016)		✓	✓		✓				✓	
Park et al. (2015)		✓	✓		✓	✓			✓	✓
Kang & Kim (2015)						✓				✓
Ochieng (2015)	✓	✓	✓	✓			✓	✓	✓	
Total	4	9	7	4	9	7	5	5	6	5

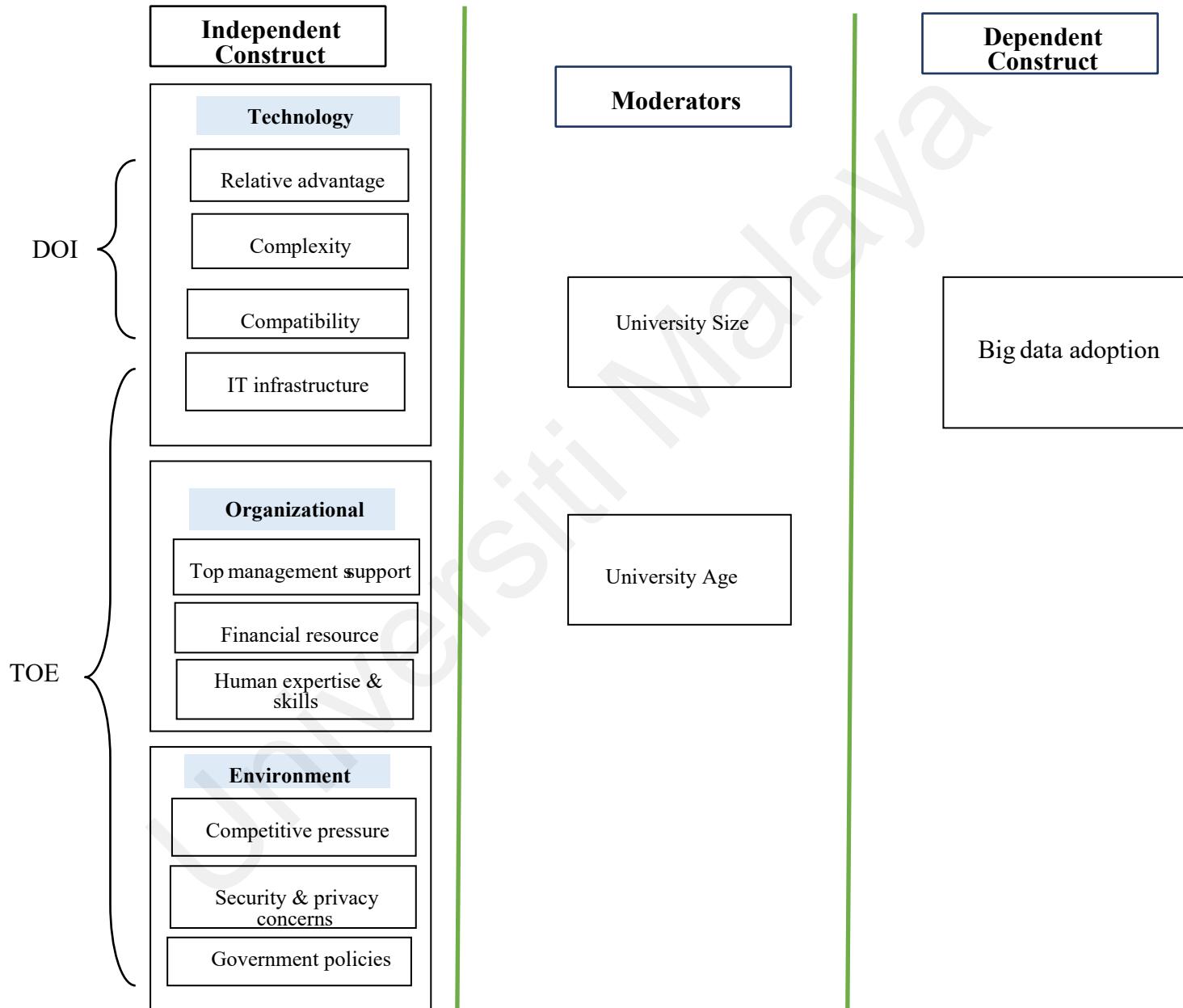


Figure 4.1: Factors for Big Data Adoption Model

2.4 Selected Factors for the Model

The justification of selected factors is given below.

▪ Technology Factors

Rogers proposed the diffusion of innovation theory in 1983. This theory suggests five attributes: relative advantage, compatibility, complexity, trialability, and observability that can affect adoption decisions (Rogers, 2003). However, trialability is most commonly used in the pre-adoption stage (Rogers, 1995). Extant literature shows that observability is related to the post-adoption stage (Rogers, 2010). Moreover, relative advantages, complexity, and compatibility are significantly used in the adoption stage (Moore & Benbasat, 1991). This study focuses on the adoption of big data in the higher education sector. Therefore, relative advantages, complexity and compatibility were included from in the diffusion of innovation theory in a technology setting.

a. Relative Advantage

Relative advantages refer to ‘superiority’, at which new technology appears supreme to existing technology (Tornatzky, Fleischer, & Chakrabarti, 1990). An innovation might be received if it outperforms what it overrides. In the education sector, adoption decisions are related to assessing the benefits of innovative technology (Al-araibi, Mahrin, & Yusoff, 2019). Big data adoption provides many advantages to the adopters in terms of time and cost as well as better decision-making (AlAjmi et al., 2018). Relative advantage is a significant big data adoption indicator that assists in achieving objectives more successfully (Yadegaridehkordi et al., 2020). Notwithstanding, in the majority of the prior studies, it has been significantly connected with the different innovation adoption in the higher

education sector (AlAjmi, Arshah, Kamaludin, Sadiq, & Al-Sharafi, 2017). In the adoption context, it has been utilized to expand the chances and improve administrative tasks (Nadal et al., 2019; Ullah et al., 2021). Relative advantage is helpful in better comprehension of the overall managerial positions (Sun, Cegielski, Jia, & Hall, 2018). It can improve the probability of designation of the administrators, which is important the maintenance and utilization of assets in technological advancement (Baig et al., 2019). In this study, the relative advantage is used to check the relationship with big data adoption in higher education.

b. Complexity

Complexity refers to technological advancement that is perceived to be difficult to comprehend and apply (Rogers, 2003). Innovations that appear simple to utilize have a superior possibility of being adopted (Ghasemaghaei & Calic, 2020). The technology that is too complex, there is a high possibility of rejection of adopting that technology (Caesarius & Hohenthal, 2018). However, complexity has been found to be a more significant factor for big data adoption studies (Yadegaridehkordi et al., 2018). On the other hand, several educational studies showed a consistent and significant relationship between complexity and technology adoption (Al-araibi, Naz'ri bin Mahrin & Yusoff, 2019; Hiran & Henten, 2019). In the big data adoption context, technological complexity has been tested in organizations, businesses, supermarkets, and firms (Nyeko & Ogenmungu, 2017; Sun, Cegielski, Jia, & Hall, 2018). Therefore, in this study, complexity is used to check the relationship with big data adoption in higher education.

c. Compatibility

It refers to advancement that fits with adopters' current values, needs, and past practices (Rogers, 2003). A broad measure of research exists that focuses on compatibility. The extant literature highlights that compatibility could be a vital determinant of IT adoption. However, incongruent qualities and standards of technology won't be embraced as quickly as an advancement that is viable. Compatibility has been considered an important construct for big data adoption and the education sector. Yadegaridekordi et al. (2020) discovered compatibility to be a significant determinant of big data adoption context. The huge amount of data storage brings innovations that can change universities' work practices (Baig et al., 2020). Therefore, it is highly important that innovative progression and changes are compatible with the existing set-up so that the proprietor can easily adopt the new innovative advancement. Therefore, in this study, compatibility is used to check the relationship with big data adoption in higher education.

d. IT Infrastructure

IT infrastructure refers to tools necessary for IT arrangements and administrations to its representatives (Arfat et al., 2020). It usually includes software, hardware, and network-related resources (Aldowah, Al-Samarraie, Alzahrani, & Alalwan, 2019). IT infrastructure facilitates the institutions by providing the equipment needed for programming and extensions in further correspondence (Raguseo, 2018). The extant literature provides insight that IT infrastructure plays a vital role that bridging a gap for investors in innovation adoption (Yadegaridehkordi et al., 2020). IT infrastructure is helpful to minimizing the irregularities and barriers by creating cross-functional channels for adoption in the education sector (Rajak et al.,

2018). Therefore, in this study, IT infrastructure is used to check the relationship with big data adoption in higher education.

▪ **Organization Factors**

The organizational factor is one of the most broadly contemplated factors in adoption research. The organizational factors employed in this research are top management support, financial resources, human expertise and skills.

a. *Top Management Support*

Top management refers to senior management that provides support and facilitates management related issues (Albarghouthi, Qi, Wang, & Abbad, 2020). The extant literature showed that top management support is one of the most significant factors of technological adoption (Hsu, Liu, Tsou, & Chen, 2019).

Top management support is essential in institutions as it makes an interpretation in structures and administrative activities for advancement (Hernandez, 2020). Top managers are answerable for changing the standards, qualities, and culture inside an organization (Yadegaridehkordi et al., 2020). The standards, qualities, and culture induced by the top administration pervade the individual level as strategies, rules, guidelines, and schedules.

It fills in as ground-breaking layouts that control singular conduct (Kashada, Li, & Koshadah, 2018). Top management support can be a positive environment for technological adoption in the educational sector (Bervell & Umar, 2017). Therefore, in this study, top management support is used as a factor to check the relationship with big data adoption in the higher education sector.

b. Financial Resources

Financial resources refer to funds and assets needed for the execution of current expenses and costs for extended propagation (Rhodes, Aguilar, Jose, & Gold, 2018). Financial resources are the most frequently examined factor by different adoption studies (Almaiah et al., 2020). Financial resources play a significant role in adoption decisions (Tarthini, Al-Gharbi, Al-Badi, & AlHinai, 2018). This factor acts as the main barrier to the adoption of innovative technology (Yadegaridehkordi et al., 2020). The previous research highlighted that technologies are adopted by organizations that have sufficient financial resources (Schuwer & Janssen, 2018). Extant studies have shown cost-effectiveness to be a highly significant factor in the adoption context (AlAjmi, Arshah, Kamaludin, Sadiq, & Al-Sharafi, 2017; Sabi et al., 2017). In educational adoption studies, it has a significant effect on technological adoption (Karia & Soliman, 2017; Mikalef et al., 2020). In this study, financial resources are used as a factor to check the relationship with big data adoption in the higher education sector.

c. Human Expertise and Skills

Human expertise refers to advanced field-related knowledge (Huda, 2019). The extant literature highlights that the adoption of innovation requires expertise and abilities as it is a time-consuming process (Liaquat & Siddiqui, 2021). The adoption process might be very deliberate if institutions lack human expertise and skills for technological adoption (Lawrence & Tar, 2018). Moreover, it is the most significant factor in technological adoption (Hamidi & Chavoshi, 2018). Adoption smoothness is dependent upon the availability of field experts (Karia & Soliman,

2017). In this study, human expertise and skills are used as a factor to check the relationship with big data adoption in the higher education sector.

▪ **Environment Factors**

In this study, competitive pressure, security and privacy concerns and government policies are added to the environmental context of the TOE framework.

a. *Competitive Pressure*

It is defined as an impact on institution motivations to embrace item and process innovations (Qasem et al., 2020). The aftereffect of competitive pressure is another institute adopting the technology (Alajmi et al., 2018). It has been found that most of the institutions adopt technology because of pressure from another institutes (Tarthini, Al-Gharbi, Al-Badi, & AlHinai 2018). On the other hand, institutions feel the need to adopt IT and use new technologies in order to maintain a competitive advantage in the educational industry (Albarghouthi et al., 2020). In this study, competitive pressure is used as a factor to check the relationship with big data adoption in the higher education sector.

b. *Security and Privacy Concerns*

Security and privacy concerns are related to the protection of data related to individuals or groups of people (Orehovački, Babić, & Etinger, 2017; Almaiah & Al-Khasawneh, 2020). The measure of data that institutions must keep secure as it is expanding day by day (Alsmadi & Prybutok, 2018). Because of technological advancement, institutions are continually increasing more information about their students (Hamzah, Mahmud, Zukri, Yaacob, Yacob, & Kelantan, 2017). They

should guarantee and ensure the information security and protection of personal data (Jawad, Ajlan, & Abdulameer, 2017). Security empowers to set limits and shield students from unjustifiable impedance in their lives (Al Harthy, Al Shuhaimi, & Al Ismaily, 2019). Security can shield from discretionary and inappropriate utilization of intensity by states, organizations, and institutions (Almaiah & Al-Khasawneh, 2020). In big data adoption research, security and privacy are the most stressed factor (Drewry, Shutske, Trechter, Luck, & Pitman, 2019). In this study, security and privacy concerns are used as a factor to check the relationship with big data adoption in the higher education sector.

c. *Government Policies*

Government policies are instructions or guidelines that are developed to protect people from potential harm (Jnr, Majid, & Romli, 2019). In technological adoption studies, government policies are a highly recommended factor (Orser, Riding, & Li, 2019). Different organizations and institutes need to follow various guidelines and principles for technological adoption (Nguyen, Greenland, Lobo, & Nguyen, 2019). Extant research shows that government policies help to adopt technology smoothly (Sun, Cegielski, Jia, & Hall, 2018). It has been found that flexible government principles will increase technological adoption (Lai, Sun, & Ren, 2018). Government policies can become a barrier to technological advancement in the education sector (Nguyen et al., 2019). Therefore, in this study, government policies are used as a factor to check the relationship with big data adoption in the higher education sector.

■ **Moderating Factors**

The use of moderators is important to consider for active relations. It allows quality improvement for technology adoption and the development of research models (Lai, Sun, & Ren, 2018). Age and size have been used in various research disciplines as moderators. However, the literature has not explored age and size moderators' effect in the big data adoption context. Therefore, these moderators were selected from the literature. Age refers to years of existence. However, size refers to the number of employees. Moderators can be helpful testing for the possible cause of content (Shin, Park, Lee, 2018). Therefore, in this study age of the university and size of the university will be used to check the effect with other independent and dependent constructs.

■ **Dependent Factor**

The dependent factor of this study is the adoption of big data. It is the outcome of this study. Adoption of big data includes cutting-edge information processing methods and tools that enhance decision-making. The adoption of big data can be achieved by models that predict compliance with other factors.

4.3 Hypotheses Development

The hypotheses of the study are developed through literature and categorized under technology, organization, and environment context.

4.3.1 Technology Context

a. Relative Advantage

Relative advantage is a profoundly important big data adoption predictor that helps to accomplish goals more effectively in higher education (Baig, Shuib, & Yadegaridehkordi, 2020). However, in most of the earlier educational research, it has been positively associated with the adoption of innovative technology (Hiran & Henten, 2019). In the big data adoption context, relative advantage has been used to increase opportunities, competitiveness, and improve user services (Sun, Cegielski, Jia, & Hall, 2018). Big data positively impacts relative advantage and proves cost-effective (Albarghouthi, Qi, Wang, & Abbad, 2020). To supersede, a novelty must be perceived as contributing advantages compared to existing services (Rokanta, 2017). The relative advantage was found to be the most important determinant that positively influences the adoption of innovative services in higher education institutions (Nyeko & Moya, 2017).

Therefore, based on the aforementioned theoretical arguments, the proposition can be hypothesized as:

H1: Relative advantage positively impacts on big data adoption.

b. Complexity

Complexity refers to a characteristic of big data that is difficult to understand and use (Verma, Bhattacharyya, & Kumar, 2018). It can be classified as simplicity or level of difficulty using innovation (Verma & Bhattacharyya, 2017; Sayginer & Ercan, 2020). However, the perception of complexity may be different among

adopters (Lai, Sun, & Ren, 2018). In educational research, complexity has been observed as a negative impact on the adoption of innovation (Singh & Mansotra, 2019). Consequently, the greater the complexity, the less likely big data adoption will be.

The complexity and adoption can be influenced by moderator size (Kang & Park, 2018). University size usually means the total number of employees. It has been proven that size is an important factor that affects the innovation diffusion factors (Alshirah et al., 2021). Salah, Yusof, & Mohamed (2021) suggested that the size factor could be useful in dealing with complexity.

Therefore, based on the above theoretical arguments, the proposition can be hypothesized as:

H2a: Complexity negatively impacts on the big data adoption.

H2b: The relationship between the complexity and big data adoption will be further strengthened by university size.

c. Compatibility

Compatibility has been identified as one of the most critical predictors in educational adoption studies (Verma & Bhattacharyya, 2017; Alajmi et al., 2018; Sayginer & Ercan, 2020). However, previous big data adoption research singles out compatibility's impact on the adoption of technological innovation (Yadegaridehkordi et al., 2020). According to Sun, Cegielski, Jia, & Hall (2018), the technology perceived should be reliable, user-friendly, and well-matched with the existing needs and demands of the user. Ansong, Sheena, & Richard (2017) indicated that organizational compatibility influences the adoption of e-learning.

Additionally, the lack of compatibility with new technology leads to uncertainty about its adoption. Age is a moderator that influences compatibility and technology adoption (Ochieng, 2015). There is evidence that the ‘age’ factor is extensively used by various studies (Kang & Park, 2018; Shin, Park, & Lee, 2018; Alshirah et al., 2021). However, more compatibility is achieved with age. Prior educational studies provided confirmation that institutions are more likely to adopt innovation that is compatible with the existing setup (Nyeko & Ogenmungu, 2017; Singh & Mansotra, 2019; Sayginer & Ercan, 2020).

Therefore, based on the above theoretical arguments, the proposition can be hypothesized as:

H3a: Compatibility positively influences big data adoption.

H3b: The relationship between compatibility and big data adoption will be further strengthened by the university age.

d. IT infrastructure

IT infrastructure is a significant factor that fulfils the organizational demands and is linked with big data adoption (Almoqren & Altayar, 2016). Big data is comprised of technological infrastructure that is related to the collection, storage, and analysis. In most cases, weak infrastructure may obstruct the analysis of the large volume of data. Strong IT infrastructure provides accurate information, which leads to the successful adoption of big data (Lai, Sun, & Ren, 2018). It can help in analyzing multisource information like weblogs and social media. The size and age strengthen the relationship between IT infrastructure and adoption (Shin et al.,

2018; Alshirah et al., 2021; Salah et al., 2021). It allows for achieving superior performance. Baig et al. (2020) highlighted that IT infrastructure positively influences e-learning adoption in universities. Nyeko & Moya (2017) suggested that IT infrastructure is a necessity for universities as it plays a significant role in technological adoptions. It imparts reliable storage, fast processing, and easy integration for big data management.

Therefore, based on the above theoretical arguments, the proposition can be hypothesized as:

H4a: IT infrastructure positively influences big data adoption.

H4b: The relationship between the IT infrastructure and big data adoption will be further strengthened by the university size.

H4c: The relationship between the IT infrastructure and big data adoption will be further strengthened by the university age.

4.3.2 Organizational Context

a. Top Management Support

“Top management support” is the degree to which it perceives the significance and relevance of big data adoption (Hernandez, 2020). Lai, Sun, & Ren (2018) argued that top management does not bolster the transformation factor and contradiction in adopting advancement. In big data adoption, process changes are required (Gunasekaran et al., 2017). When top management shows an unwillingness to

change for development, then, the entire association begins to follow higher administration decisions, which will likely delay the adoption process (Albarghouthi et al., 2020; Almaiah & Al-Khasawneh, 2020).

The executive's support is necessary to incorporate the rules, handle the information, and adopt the innovation (Liaquat & Siddiqui, 2021). Thus, management support can be a significant factor that contributes to the adoption of big data (Sun, Cegielski, Jia, & Hall, 2018). Previous research found an optimistic relationship between top management support and innovation adoption (Nyeko & Moya, 2017; Tarhini, AlGharbi, Al-Badi, & Al Hinai, 2018; Singh & Mansotra, 2019).

Therefore, based on the above theoretical arguments, it can be hypothesized as:

H5: Top management support positively influences big data adoption.

b. Financial Resources

“Financial resources” is an important determinant that distinguishes the adopter from the non-adopter (Verma & Bhattacharyya, 2017). The size shows a positive moderating effect on adoption and financial resources (Kang & Park, 2018). There will be more chances for adoption if institutes have sufficient financial resources (Mikalef et al., 2020).

Therefore, based on the above theoretical arguments, it can be hypothesized as:

H6a: Financial resources positively impact on big data adoption.

H6b: The relationship between the financial resource and big data adoption will be further strengthened by the university size.

c. *Human Expertise and Skills*

“Human expertise and skills” refer to the employees that possess the ability and IT knowledge related to the adoption of technology (Ediriweera & Wiewiora, 2021). These skills are needed in the big data utilization process (Lai, Sun, & Ren, 2018). Human expertise has played a noteworthy role in utilizing technological advancement (Nyeko & Moya, 2017; Ediriweera & Wiewiora, 2021). On the other hand, Ochieng (2015) indicated that the relationship between human expertise and skill and big data adoption is moderated by age. Strong programming and logical abilities are helpful in the adoption of big data (Yadegaridehkordi et al., 2020). Thus, sufficient human expertise and skills will increase the size of big data adoption.

Therefore, based on the above theoretical arguments, it can be hypothesized as:

H7a: Human expertise and skills positively influence big data adoption.

H7b: The relationship between human expertise and skills, and big data adoption will be further strengthened by the university age.

4.3.3 Environment Context

a. *Competitive Pressure*

Competitive pressure was found to be the major adoption determinant that indicates the intensity of competition (Albarghouthi et al., 2020). To remain competitive, managers should show a positive attitude towards big data adoption (Verma & Bhattacharyya, 2017). Nyeko & Ogenmungu, (2017) study showed a significant relationship between competitive pressure and innovation adoption. Age can moderate the relationship between competitive pressure and innovational adoption

(Asheghi-Oskooeea & Mazloomi, 2018). The education sector is pressured to adopt innovation to maintain the standard practice (Singh & Mansotra, 2019). Therefore, based on the above theoretical arguments, it can be hypothesized as:

H8a: Competitive pressure positively influences big data adoption.

H8b: The relationship between competitive pressure and big data adoption will be further strengthened by the university age.

b. Security and Privacy Concerns

Security and privacy concerns were the obstructing factors of big data adoption (Wu, Li, Liu, & Zheng, 2017; Nguyen & Petersen, 2017; Almaiah & Al-Khasawneh, 2020). It does not only affect the big data adoption process (Yadegaridehkordi et al., 2020) but also destroys its reputation (Sun, Cegielski, Jia, & Hall, 2018). Age is a moderator that influences security and privacy concerns and big data adoption (Ochieng, 2015). Previous educational research negatively correlated privacy and security and innovative adoption (Baig et al., 2020). Therefore, the lack of security and privacy can negatively affect the adoption of big data in the education sector.

Thus, based on the above theoretical arguments, it can be hypothesized as:

H9a: Security and privacy concerns' negatively impact big data adoption.

H9b: The relationship between security & privacy concerns and big data adoption will be further strengthened by the university age.

c. *Government Policies*

“Government policies” are developed to reduce potential issues, particularly those connected with individual protection (Lai, Sun, & Ren, 2018). The government should support adopters' access to data without disturbing their private values (Sun, Cegielski, Jia, & Hall, 2018). Universities ought to depict the utilization of data clearly, before adoption (Nyeko & Ogenmungu, 2017). Age refers to the time the institute has existed. Age can be moderated by government policies and technology adoption (Asheghi-Oskooeea & Mazloomi, 2018). The proper adoption of BD requires the government to analyze the rules and policies (Tarthini et al., 2018). Therefore, based on the above theoretical arguments, it can be hypothesized as:

H10 a: Government policies positively impact big data adoption.

H10 b: The relationship between Government policies and big data adoption will be further strengthened by the university age.

The relationship of the hypothesis is presented in Figure 4.2.

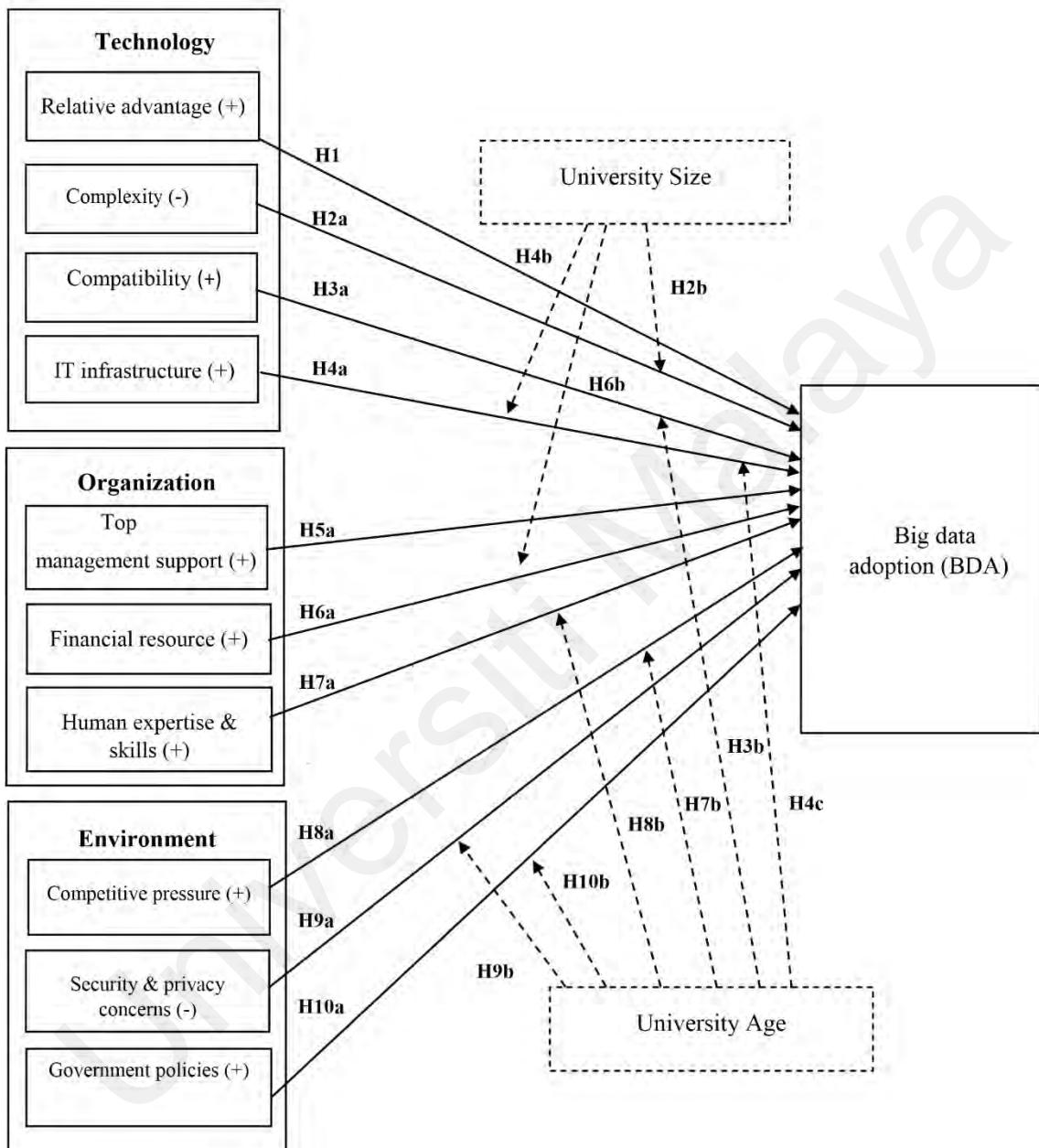


Figure 4.2: Proposed Theoretical Model for Big Data Adoption

4.4 Summary

This chapter presented the research model and the hypotheses of the study. The complete process of model development is given in this chapter. The factors that can affect big data adoption were extracted through big data adoption studies. The independent, moderating, and dependent factors were discussed. A detailed justification of selected factors was presented. The hypotheses were developed through a comprehensive literature review. Finally, the diagrammatic view of the theoretical model for big data adoption was given in this chapter. The next chapter describes in detail the data analysis and discussion of this study.

CHAPTER 5: DATA ANALYSIS AND FINDINGS

5.1 Introduction

This chapter presents the data analysis and discusses the findings. It presents the demographic analyses of respondent profile data. This study already identified the factors and developed a theoretical model through a comprehensive literature review in Chapter 3. However, in this chapter, partial least square-structural equation modelling is applied to collected data to analyze the relationship between multiple latent variables and test the hypotheses accordingly. The model assessment is performed through the measurement model (outer model) and structural model (inner model).

5.2 Demographic Analysis

In this study, data was collected from the questionnaires. The participant's profile is categorized into five sections, namely: gender, age, role, working experience, and campus age.

5.2.1 Participants Profile

The respondents' profile is acquired from the demographic information presented in the questionnaire. In total, 195 is the final sample size. 84.78% of the participants were included in this study. To increase the quality of research, only those responses were considered based on their familiarity with big data. However, 15.22% were excluded from the study population as they were unfamiliar with big

data. The majority of participants consisted of 89.23% males and 10.76% females. 18.97% of participants' ages fell between (18-25), 44.10% fell at the age of (26-35), and 27.69% were lying under (36-50), while 9.23% were above 51-years and below 65-years of age. 10.76% were database administrators, 11.79% were campus administrators, 23.58% were IT administrators, and 53.84% were network administrators or associate network administrators. 17.43% of participants had less than one year of experience, 39.48% had greater than 1 but less than 5 years of experience, and 32.82% of participants had the experience of somewhere in between 6 to 10 years, 8.20% of participants' experience varied between 11 to 15 years of experience, while 2.05% had more than 15 years of experience. A total of 81 campuses responded to questionnaires. However, most campuses have existed for the last 6 to 10 years. The result summary of the descriptive analysis (participant profile) is presented in Table 5.1.

Table 5.1: Descriptive Analysis (Respondents' Profiles)

Categories	Sub-categories	Frequency	Percentage
Gender	Male	174	89.23%
	Female	21	10.76%
Age	18 to 25	37	18.97%
	26 to 35	86	44.10%
	36 to 50	54	27.69%
	51 to 65	18	9.23%
Role	Database Administrator	21	10.76%
	Campus Administrator	23	11.79%
	IT administrator	46	23.58%
	Network Administrator/ Associate Network Administrator	105	53.84%
Working experience	Less than one year	34	17.43%
	1 to 5 years	77	39.48%
	6 to 10 years	64	32.82%
	11 to 15 years	16	8.20%
	More than fifteen years	4	2.05%
Campus Age	Less than one year	1	0.52%
	1 to 5 years	18	9.23%
	6 to 10 years	56	29.47%
	11 to 15 years	4	5.78%
	More than 15 years	2	7.89%

5.3 Model Assessment

5.3.1 Measurement Model (Outer-Model) Assessment

In the first stage of model analysis, the model reliability is tested. Cronbach's alpha, and a composite reliability value greater than 0.7 were acceptable. Table 5.2 shows that the factor loadings, Cronbach's alpha and composite reliability of all items and constructs are greater than 0.7. These results confirmed construct reliability.

Table 5.2: Results of the Factor Loading, Reliability, and Convergent Validity

Constructs	Item	Factor Loading (>0.7)	Reliability		Convergent Validity AVE (>0.5)
			Cronbach's Alpha (>0.7)	Composite Reliability (>0.7)	
BDA	BDA1	0.88	0.83	0.89	0.67
	BDA2	0.76			
	BDA3	0.85			
	BDA4	0.77			
Relative Advantage	RA1	0.90	0.91	0.94	0.79
	RA2	0.90			
	RA3	0.89			
	RA4	0.86			
Complexity	Complex 2	0.75	0.71	0.84	0.63
	Complex 3	0.78			
	Complex 4	0.84			
Compatibility	Compat1	0.89	0.92	0.94	0.80
	Compat2	0.85			
	Compat3	0.88			
	Compat4	0.92			
IT infrastructure	ITinf1	0.89	0.89	0.93	0.76
	ITinf2	0.79			
	ITinf3	0.90			
	ITinf4	0.88			

Table 5.2: Results of the Factor Loading, Reliability, and Convergent Validity (Con't)

Constructs	Item	Factor Loading (>0.7)	Reliability		Convergent Validity AVE (>0.5)
			<i>Cronbach's Alpha (>0.7)</i>	<i>Composite Reliability (>0.7)</i>	
Top Management Support	TMS1	0.97	0.95	0.96	0.87
	TMS2	0.91			
	TMS3	0.94			
	TMS4	0.91			
Financial Resource	FR1	0.94	0.92	0.94	0.81
	FR2	0.82			
	FR3	0.91			
	FR4	0.89			
Competitive Pressure	CP1	0.83	0.84	0.89	0.68
	CP2	0.89			
	CP3	0.85			
	CP4	0.71			
Human Expertise and Skills	HE1	0.79	0.84	0.89	0.67
	HE2	0.88			
	HE3	0.85			
	HE4	0.75			
Security & Privacy	SP1	0.87	0.89	0.93	0.76
	SP2	0.85			
	SP3	0.88			
	SP4	0.88			

Table 5.2: Results of the Factor Loading, Reliability, and Convergent Validity (Con't)

Constructs	Item	Factor Loading (>0.7)	Reliability		Convergent Validity AVE (>0.5)
			Cronbach's Alpha (>0.7)	Composite Reliability (>0.7)	
Government Policies	GP1	0.91	0.90	0.93	0.76
	GP2	0.92			
	GP3	0.85			
	GP4	0.80			
University Age	UA1	0.81	0.85	0.90	0.69
	UA2	0.87			
	UA3	0.82			
	UA4	0.83			
University Size	US1	0.89	0.90	0.93	0.77
	US2	0.88			
	US3	0.83			
	US4	0.91			

(RA=Relative Advantage, BDA = big data adoption, Complex = complexity, Compat = compatibility, IT inf = information technology infrastructure, TMS = top management support, FR = financial resources, HE = human expertise and skills, CP = competitive advantage, SP = security and privacy concerns, GP = government policies, US = university size, UA= university age)

Secondly, the convergent validity was assessed with the help of the average variance extracted (AVE). The value of AVE is equal to or greater than 0.5 is considered (Hair et al., 2016). The results of this study found that all the AVE values exceeded the threshold of 0.5. It ranged from 0.67 to 0.87, which ascertained the convergent validity. Table 5.3 presents the results of this test.

The Fornell-Larcker criterion, cross-loading criterion, and heterotrait-monotrait ratio were analyzed to test the discriminant validity. The Fornell-Larcker criterion results table is given in Table 5.3. It has been found that the square root of AVE is greater than any of the co-related construct correlations. Therefore, it confirmed the

highest variance with its co-related items. Thus, the results reflected an acceptable correlation by comparing construct values in terms of rows and columns.

The Heterotrait-monotrait results table is given in Table 5.4. According to AbHamid, Sami, & Sidek (2017), the heterotrait-monotrait values of less than 0.90 are acceptable. The results showed that all constructs' values in terms of rows and columns were less than 0.90. Therefore, it confirms the validity of constructs.

The cross-loadings results table is given in Table 5.5. The results indicated that the cross-loadings results reflected that factor loading of all construct items was greater than other loadings in terms of row and column.

Table 5.3: Fornell-Larcker Criterion

	BDA	GP	Complex	Compat	ITinf	TMS	FR	HE	CP	SP	RA	US	UA
BDA	0.82												
GP	0.33	0.87											
Complex	0.53	0.13	0.79										
Compat	0.55	0.19	0.58	0.90									
ITinf	0.53	0.25	0.57	0.60	0.87								
TMS	0.63	0.21	0.52	0.36	0.45	0.93							
FR	0.61	0.23	0.54	0.55	0.55	0.62	0.90						
HE	0.65	0.23	0.58	0.45	0.53	0.67	0.69	0.82					
CP	0.28	0.09	0.24	0.13	0.14	0.23	0.21	0.33	0.83				
SP	0.44	0.34	0.44	0.39	0.47	0.63	0.67	0.71	0.23	0.87			
RA	0.29	0.60	0.17	0.14	0.20	0.18	0.22	0.18	0.11	0.27	0.89		
US	0.46	0.18	0.48	0.28	0.30	0.61	0.40	0.53	0.11	0.53	0.15	0.88	
UA	0.54	0.22	0.56	0.39	0.43	0.63	0.63	0.75	0.38	0.74	0.20	0.55	0.83

Note: Bold diagonal elements represent the Average Variance Extracted (AVEs) for the relevant construct.

(RA= relative advantage, BDA = big data adoption, Complex = complexity, Compat = compatibility, IT inf = information technology infrastructure, TMS = top management support, FR = financial resources, HE = human expertise and skills, CP = competitive advantage, SP = security and privacy concerns, GP = government policies, US = university size, UA= university age)

Table 5.4: Heterotrait-Monotrait Ratio (HTMT)

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. BDA													
2. GP	0.3												
3. Complex	0.6	0.16											
4. Compat	0.6	0.21	0.71										
5. ITinf	0.5	0.27	0.69	0.66									
6. TMS	0.7	0.23	0.62	0.38	0.47								
7. FR	0.6	0.25	0.66	0.60	0.59	0.66							
8. HE	0.7	0.26	0.75	0.51	0.58	0.74	0.78						
9. CP	0.3	0.11	0.31	0.15	0.16	0.25	0.24	0.39					
10. SP	0.5	0.37	0.54	0.43	0.51	0.68	0.74	0.83	0.26				
11. RA	0.3	0.67	0.21	0.16	0.21	0.19	0.24	0.19	0.13	0.29			
12. US	0.5	0.19	0.59	0.30	0.30	0.64	0.41	0.59	0.11	0.57	0.16		
13. UA	0.6	0.25	0.68	0.44	0.48	0.69	0.70	0.89	0.46	0.85	0.22	0.61	

(BDA = big data adoption, RA= relative advantage, Complex = complexity, Compat = compatibility, IT inf = information technology infrastructure, TMS = top management support, FR = financial resources, HE = human expertise and skills, CP = competitive advantage, SP = security and privacy concerns, GP = government policies, US = university size, UA= university age)

Table 5.5: Cross Loading

	BDA	CP	Compat	Complex	FR	GP	HR	IT inf	RA	SP	TMS	UA	US
BDA1	0.78	0.75	0.57	0.48	0.69	0.61	0.77	0.63	0.69	0.67	0.64	0.62	0.71
BDA2	0.80	0.62	0.61	0.50	0.58	0.64	0.60	0.65	0.58	0.65	0.70	0.55	0.59
BDA3	0.79	0.47	0.69	0.56	0.47	0.63	0.48	0.61	0.60	0.51	0.50	0.40	0.60
BDA4	0.81	0.57	0.68	0.57	0.53	0.62	0.46	0.64	0.64	0.56	0.56	0.51	0.58
CP1	0.65	0.86	0.51	0.47	0.70	0.62	0.78	0.67	0.66	0.65	0.66	0.60	0.76
CP2	0.61	0.87	0.57	0.52	0.71	0.61	0.77	0.56	0.67	0.62	0.58	0.65	0.73
CP3	0.62	0.76	0.67	0.71	0.62	0.68	0.57	0.63	0.64	0.59	0.62	0.56	0.65
CP4	0.70	0.87	0.56	0.50	0.68	0.59	0.78	0.59	0.76	0.69	0.68	0.68	0.76
Compat1	0.75	0.59	0.87	0.62	0.60	0.60	0.52	0.67	0.68	0.60	0.57	0.53	0.64
Compat2	0.66	0.57	0.85	0.74	0.54	0.65	0.51	0.64	0.65	0.51	0.54	0.50	0.65
Compat3	0.62	0.63	0.80	0.70	0.63	0.61	0.64	0.62	0.65	0.62	0.61	0.55	0.67
Compat4	0.62	0.50	0.81	0.58	0.52	0.67	0.51	0.59	0.60	0.51	0.56	0.46	0.50
Complex2	0.56	0.63	0.59	0.80	0.65	0.64	0.55	0.56	0.68	0.61	0.59	0.55	0.63
Complex3	0.51	0.44	0.67	0.82	0.46	0.65	0.38	0.48	0.47	0.41	0.40	0.32	0.47
Complex4	0.54	0.51	0.66	0.81	0.46	0.70	0.49	0.58	0.60	0.48	0.53	0.43	0.55
FR1	0.65	0.54	0.55	0.59	0.85	0.62	0.72	0.61	0.65	0.56	0.64	0.64	0.75
FR2	0.57	0.58	0.59	0.53	0.83	0.61	0.75	0.58	0.62	0.50	0.62	0.65	0.63
FR3	0.70	0.69	0.62	0.50	0.81	0.60	0.70	0.66	0.63	0.57	0.64	0.62	0.66
FR4	0.61	0.64	0.57	0.58	0.89	0.63	0.75	0.60	0.69	0.54	0.66	0.69	0.68
GP1	0.65	0.70	0.57	0.55	0.73	0.73	0.82	0.65	0.62	0.53	0.67	0.63	0.75
GP2	0.68	0.58	0.68	0.62	0.61	0.82	0.55	0.67	0.60	0.65	0.62	0.53	0.67
GP3	0.52	0.44	0.67	0.68	0.40	0.76	0.35	0.58	0.48	0.41	0.38	0.33	0.50
GP4	0.51	0.42	0.72	0.67	0.42	0.74	0.43	0.54	0.53	0.38	0.38	0.36	0.43
HR1	0.59	0.73	0.57	0.53	0.68	0.61	0.86	0.58	0.60	0.61	0.65	0.65	0.73
HR2	0.72	0.62	0.57	0.51	0.72	0.67	0.87	0.61	0.63	0.63	0.63	0.67	0.73
HR3	0.51	0.70	0.52	0.49	0.70	0.58	0.77	0.47	0.66	0.60	0.65	0.69	0.66
HR4	0.61	0.65	0.50	0.43	0.76	0.55	0.81	0.58	0.66	0.62	0.66	0.64	0.63
ITinf1	0.53	0.39	0.47	0.29	0.42	0.44	0.38	0.71	0.45	0.47	0.42	0.45	0.46
ITinf2	0.64	0.55	0.70	0.67	0.61	0.72	0.53	0.78	0.59	0.58	0.58	0.52	0.57
IT inf3	0.47	0.46	0.42	0.40	0.46	0.48	0.37	0.71	0.42	0.49	0.42	0.39	0.46
ITinf4	0.76	0.61	0.65	0.60	0.66	0.73	0.69	0.83	0.69	0.68	0.64	0.62	0.71
RA1	0.67	0.69	0.59	0.58	0.76	0.64	0.82	0.65	0.83	0.60	0.60	0.69	0.72
RA2	0.66	0.63	0.54	0.53	0.69	0.57	0.70	0.51	0.81	0.72	0.69	0.74	0.70
RA3	0.67	0.68	0.67	0.60	0.73	0.64	0.70	0.62	0.83	0.61	0.72	0.68	0.70
RA4	0.53	0.41	0.69	0.67	0.39	0.62	0.35	0.55	0.71	0.39	0.35	0.30	0.43
SP1	0.58	0.57	0.55	0.47	0.71	0.58	0.72	0.54	0.69	0.78	0.72	0.70	0.69
SP2	0.68	0.65	0.56	0.47	0.72	0.61	0.77	0.63	0.74	0.89	0.81	0.71	0.75
SP3	0.69	0.56	0.58	0.51	0.59	0.59	0.52	0.69	0.61	0.73	0.59	0.51	0.58
SP4	0.61	0.70	0.49	0.56	0.75	0.59	0.74	0.56	0.68	0.84	0.75	0.70	0.70

Table 5.5: Cross Loading (con't)

	BDA	CP	Compat	Complex	FR	GP	HR	IT inf	RA	SP	TMS	UA	US
TMS1	0.62	0.66	0.51	0.46	0.76	0.53	0.74	0.57	0.64	0.53	0.86	0.76	0.68
TMS2	0.74	0.68	0.61	0.52	0.63	0.67	0.65	0.61	0.60	0.50	0.88	0.61	0.64
TMS3	0.62	0.52	0.57	0.49	0.74	0.58	0.80	0.62	0.61	0.61	0.80	0.69	0.71
TMS4	0.70	0.75	0.62	0.65	0.74	0.68	0.78	0.60	0.74	0.68	0.87	0.69	0.65
UA1	0.63	0.72	0.52	0.45	0.76	0.58	0.79	0.60	0.68	0.64	0.78	0.90	0.66
UA2	0.65	0.74	0.55	0.44	0.74	0.55	0.78	0.58	0.72	0.63	0.74	0.87	0.60
UA3	0.63	0.74	0.54	0.47	0.78	0.57	0.74	0.55	0.68	0.62	0.69	0.85	0.63
UA4	0.64	0.81	0.53	0.51	0.80	0.61	0.79	0.60	0.75	0.57	0.78	0.87	0.72
US1	0.70	0.68	0.55	0.48	0.68	0.63	0.75	0.63	0.67	0.65	0.76	0.68	0.84
US2	0.65	0.70	0.67	0.59	0.59	0.68	0.59	0.68	0.66	0.64	0.60	0.53	0.77
US3	0.58	0.70	0.60	0.57	0.64	0.58	0.62	0.52	0.60	0.62	0.59	0.61	0.76
US4	0.58	0.69	0.56	0.54	0.67	0.63	0.69	0.56	0.68	0.67	0.67	0.68	0.82

(BDA = big data adoption, RA= relative advantage, Complex = complexity, Compat = compatibility, IT inf = information technology infrastructure, TMS = top management support, FR = financial resources, HE = human expertise and skills, CP = competitive advantage, SP = security and privacy concerns, GP = government policies, US = university size, UA= university age)

5.3.2 Structural Model (Inner-Model) Assessment

The next step is structural model measurement. The structural model is analyzed after testing the outer model. The bootstrapping process was performed to test the hypothesis based on the direct and moderating effects. In the inner model, the measurement value of the path coefficient and p-values were analyzed. The path coefficient values indicate the effect of a variable occurring on another variable. The hypothesis' stated direction (negative or positive) is tested by path coefficient values signs. If the p-value is significant ($p < 0.05$), but the path-coefficient (β value) sign is different from the hypothesis stated, then the hypothesis will be rejected (Hair et al., 2017). The p-values are the probabilities of rejecting or accepting hypotheses. In previous big data adoption studies, the cutoff of the significance level of 5% was used. Therefore, the accepted p-value of this study is also 0.05 (5%).

a. Direct Relationships

Table 5.6 shows the results of the direct relationship hypotheses. In technology context, Relative advantage ($\beta = 0.117$ and $p < 0.05$), complexity ($\beta = -0.216$ and $p < 0.05$), and compatibility ($\beta = 0.158$ and $p < 0.05$) showed significant effects on big data adoption. Therefore, H1, H2a, and H3a were accepted. Conversely, the effect of IT infrastructure on big data adoption ($\beta = 0.028$ and $p > 0.05$) was not significant. Thus, H4a is rejected. From the organizational perspective, top management support ($\beta = 0.282$ and $p < 0.001$), financial resources ($\beta = 0.171$ and $p < 0.01$), and human resources ($\beta = 0.233$ and $p < 0.001$) significantly impacted big data adoption. Therefore, hypotheses H5, H6a, and H7a were supported. The environmental factors, competitive advantage ($\beta = 0.124$ and $p < 0.05$), security

and privacy concerns ($\beta = -0.359$ and $p < 0.001$) and government policy ($\beta = 0.158$ and $p < 0.01$) showed significant effects of big data adoption.

Therefore, hypothesis H8a, H9a, and H10a were also accepted.

Table 5.6: Results of Hypotheses (Direct Relationships)

Hypotheses	Path Co-efficient	Standard Deviation	t-values	p-values	Status	Decision
H1: RA → BDA	0.117	0.059	1.988	0.024	p< 0.05	Accepted
H2a: Complex → BDA	-0.216	0.094	2.294	0.011	p< 0.05	Accepted
H3a: Compat → BDA	0.158	0.086	1.837	0.033	p< 0.05	Accepted
H4a: IT inf → BDA	0.028	0.070	0.396	0.346	P>0.05	Rejected
H5: TMS → BDA	0.282	0.072	3.894	0.000	p< 0.001	Accepted
H6a: FR → BDA	0.171	0.072	2.384	0.009	p< 0.01	Accepted
H7a: HE → BDA	0.233	0.069	3.381	0.000	p< 0.001	Accepted
H8a: CP → BDA	0.124	0.058	2.156	0.016	p< 0.05	Accepted
H9a: SP → BDA	-0.359	0.074	4.839	0.000	p< 0.001	Accepted
H10a: GP → BDA	0.158	0.063	2.523	0.006	p< 0.01	Accepted

Note: *p< 0.05, **p< 0.01 and ***p< 0.001

(RA= relative advantage, BDA = big data adoption, Complex = complexity, Compat = compatibility, IT inf = information technology infrastructure, TMS = top management support, FR = financial resources, HE = human expertise and skills, CP = competitive advantage, SP = security and privacy concerns, GP = government policies)

b. Moderation Effects

Table 5.7 presents the results of moderating effects of university age and university size on relationships between technology, organization, and environment factors and big data adoption. Hypotheses H2b, H4c and H6b show negative β values (-0.147), (-0.217), and (-0.171), respectively. Thus, H2b, H4c, and H6b were rejected. The moderating effects of university age on compatibility, human expertise and skills and competitive pressure and big data adoption ($\beta = 0.036$, $\beta = -0.036$ and $p > 0.05$) were not significant. Therefore, H3b, H7b, H8b was rejected.

The moderating effects of university size on IT infrastructure, and university age on security and privacy concerns, and government policies ($\beta = 0.155$, $\beta = 0.194$, $\beta = 0.113$ and $p < 0.05$) were significant. Hence, H4b, H9a and H10b were accepted.

Table 5.7: Results of Hypotheses (Moderating Relationships)

Hypotheses	Path Co-efficient	Standard Deviation	t- values	p-values	Status	Decision
H2b: Complex * US → BDA	-0.147	0.074	1.968	0.025	$p < 0.05$	Rejected
H3b: Compat* UA → BDA	0.036	0.084	0.426	0.335	$p > 0.05$	Rejected
H4b: IT inf* US → BDA	0.155	0.082	1.894	0.029	$p < 0.05$	Accepted
H4c: IT inf * UA → BDA	-0.217	0.084	2.586	0.005	$p < 0.01$	Rejected
H6b: FR* US → BDA	-0.171	0.072	2.366	0.009	$p < 0.01$	Rejected
H7b: HE* UA → BDA	-0.036	0.088	0.410	0.341	$p > 0.05$	Rejected
H8b: CP * UA → BDA	0.032	0.051	0.622	0.267	$p > 0.05$	Rejected
H9a: SP * UA → BDA	0.194	0.089	2.180	0.015	$p < 0.05$	Accepted
H10b: GP * UA → BDA	0.113	0.051	2.213	0.014	$p < 0.05$	Accepted

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(US = university size, UA = university age, BDA = big data adoption, Complex = complexity, Compat = compatibility, IT inf = information technology infrastructure, FR= financial resources, HE= human expertise and skills, CP= competitive advantage, SP= security and privacy concerns, GP = government policies)

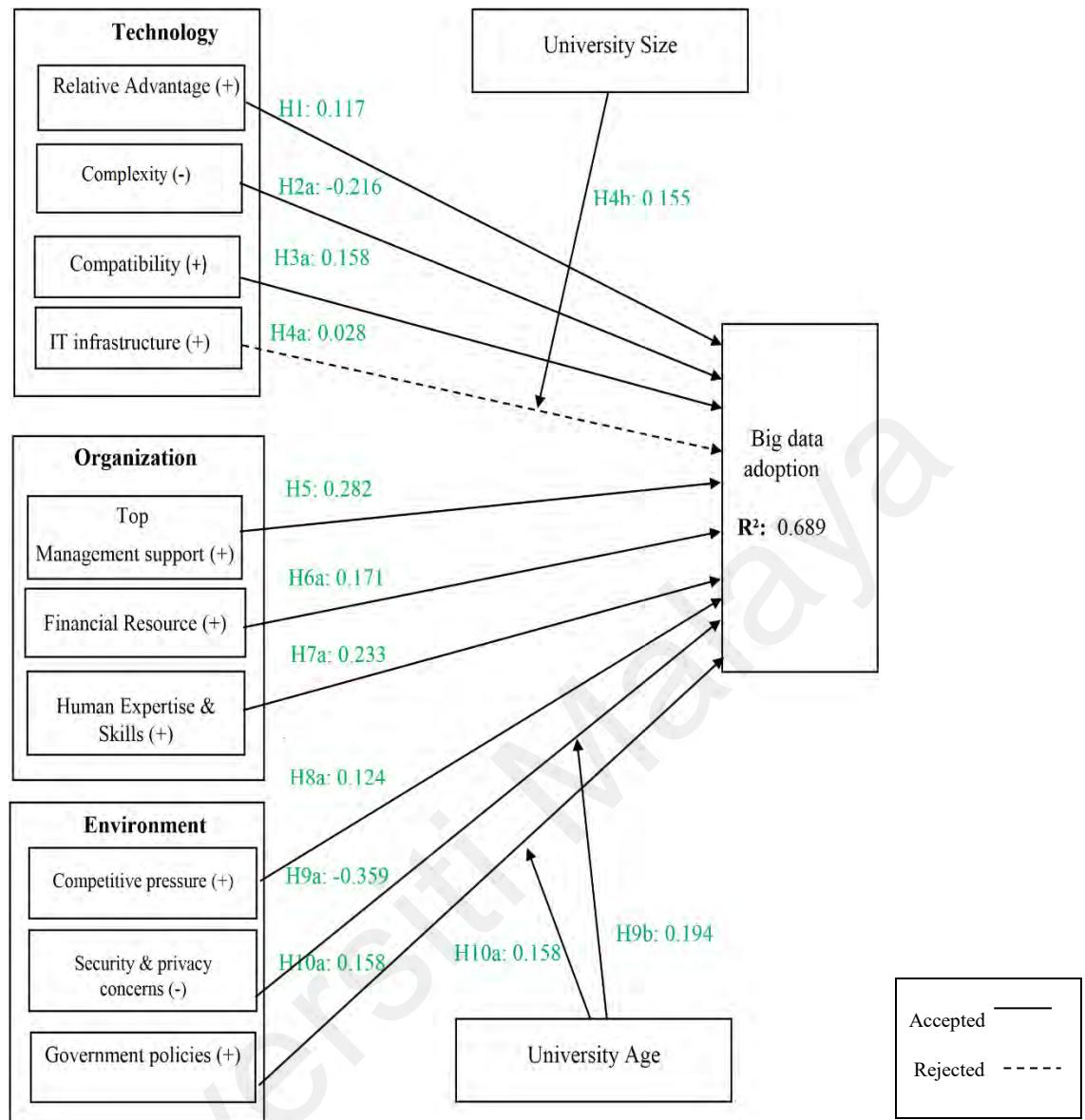


Figure 5.1: Theoretical Model for Big Data Adoption (with hypothesis)

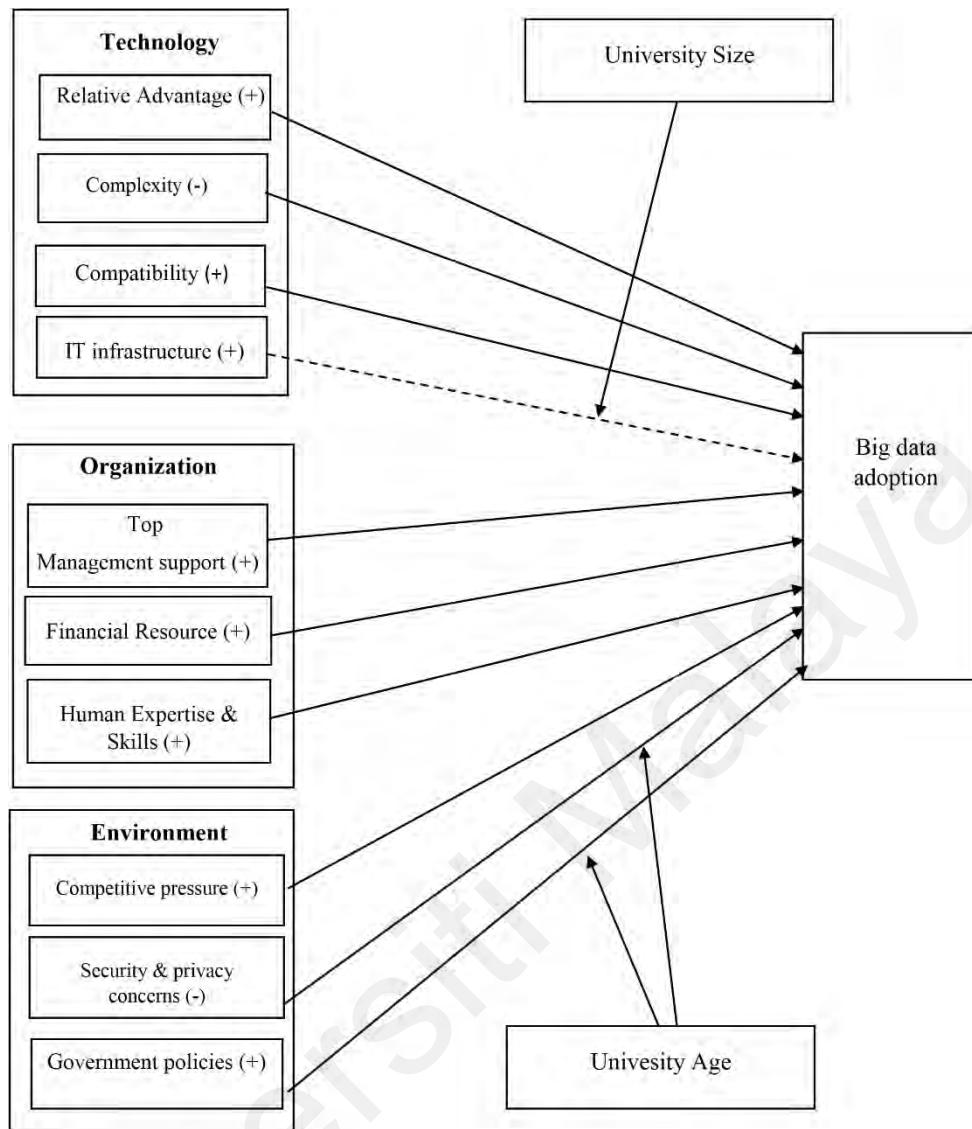


Figure 5.2: Theoretical Model for Big Data Adoption

R^2 is used to analyze the power of the model (Rigdon, Sarstedt, & Ringle, 2017). Chin (1998) described that the value of R^2 (0.67) is strong, (0.33) is moderate, and (0.19) is weak. The R^2 value of big data adoption was 0.689. The result indicates a strong predictive power of the model. It indicates that the proposed model explained 68.9 % of the variance (Figure 5.1).

5.4 Summary

In this chapter, the results of the data analysis were presented. The demographic analyses are performed. This study shows the managerial side participation of VU campuses. In total, 84.78% of responses were included in this study. The characteristics of respondent profiles were present under five categories (Gender, Age, Role, Experience, and Campus Age). In addition, the results of the model's analyses concluded that there was a strong predictive power of the big data adoption model in the education sector. In total, twelve out of nineteen hypotheses showed a significant relationship with big data adoption. In the next chapter, the discussion of the findings is presented.

CHAPTER 6: DISCUSSION

This study develops a big data adoption model for the educational sector by incorporating TOE and DOI frameworks. This is the major contribution of this research. This study found that twelve out of nineteen hypotheses were significant. Relative advantage, complexity, compatibility, top management support, financial resources, human expertise and skills, competitive pressure, security and privacy, and government policies were significant factors of big data adoption. Likewise, university age and size were found to have significant moderating effects on big data adoption. It has been found that the majority of the respondents were male, based on the population surveyed. According to the World Bank 's collection of development indicators, the labour force of Pakistan's females was reported at 20.16 percent in 2021. So, the male work force is dominant in Pakistan (Mia, 2021). Therefore, fewer female respondents in the survey are well justified. According to the findings, the majority of respondents were network administrators between the ages of 26 and 35. The majority of respondents had 1 to 5 years of working experience. Moreover, the majority of campus ages ranged from 6 to 10 years.

6.1 Technology Factors and Hypotheses

The results of the technology factors were significant and influenced big data adoption. The result indicated that relative advantage, complexity, and compatibility are significantly related to big data adoption and obtained acceptable p-values. However, information technology infrastructure had insignificant relation with big data adoption. Moreover, results indicated that one out of four moderating effects showed a significant relationship. University size strengthened the relationship between information technology infrastructure and big data adoption. However, the effects of university age on information technology infrastructure, compatibility, and big data adoption are insignificant. Similarly, insignificant moderating effects of university size between complexity and big data adoption were found.

6.1.1 Relative Advantage

The study found that relative advantage obtained accepted thresholds in a measurement model and structural model assessment. The results of the measurement model and structural model are presented in Table 6.1. Moreover, the results of this study revealed that the relative advantage has a positive impact on big data adoption. The value of p is less than 0.05. It is showing its significant relationship with big data adoption. Big data provides significant advantages to institutions, such as greater control over work to accomplish tasks more quickly and an increase in data storage (Matsebula & Mnkandla, 2016). However, this result is similar to that of earlier research (Tashkandi et al., 2015; Alajmi et al., 2018; Hiran et al., 2019; Yadegaridehkordi et al., 2020). Apparently, without the obvious distinctive relative advantages, there would not have been any rationale for

adopting big data. This result also describes the significance of relative advantage indicators in big data adoption.

Table 6.1: Relative Advantage Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
	0.91	0.94	0.79
Discriminant Validity			
Structural Model Results	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.90	0.89	0.29
	0.90		
	0.89		
	0.86		
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	0.117	0.024	

6.1.2 Complexity

The study found that complexity obtained accepted thresholds in the measurement model and structural model assessment. However, insignificant university size moderation effects were found between complexity and big data adoption. The results of the measurement model and structural model are presented in Table 6.2. In this study, the relationship of complexity was negatively associated with big data adoption. This study found a significant relationship between complexity and big data adoption. This entails complications in recognizing the utilization of big data at the adoption stage (Ochieng, 2015). Furthermore, extant literature discussed in Chapter Two has shown that complexity can negatively impact big data adoption. If the big data adoption process is less complex, then there will be more chances for the education sector to adopt it smoothly (Qasem et al., 2020). On the contrary, university size did not fortify the relationship between complexity and big data

adoption. The reason for this finding may be the difficulty of the employees in realizing the level of complexity at the initial stages.

Table 6.2: Complexity Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
	0.71	0.84	0.63
Discriminant Validity			
Structural Model Results	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.75	0.79	0.16
	0.78		
	0.84		
Complexity → Big data adoption			
Path Co-efficient (β -value)	Path Co-efficient (β -value)		P-Value
	-0.216		0.011
	Complexity * University Size → Big data adoption		
Path Co-efficient (β -value)	Path Co-efficient (β -value)		P-Value
	-0.147		0.025

6.1.3 Compatibility

The study found that compatibility obtained accepted thresholds in a measurement model and structural model assessment. The result of the measurement model and structural model is presented in Table 6.3. Regarding the compatibility factor, this study results correlated with the previous big data adoption studies (e.g., Verma & Bhattacharyya, 2017; Sun, Cegelski, Jia, & Hall, 2018). Likewise, the age of the university did not strengthen the relationship between compatibility and big data adoption. The compatibility component is a very important factor that comes with like-mindedness in all manners to achieve common work objectives. Institutes should hire faculty that perfectly fits their objective, culture, and norms.

Table 6.3: Compatibility Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
0.92	0.94	0.80	
Discriminant Validity			
Structural Model Results	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.89 0.85 0.88 0.92	0.90	0.71
	Compatibility → Big data adoption		
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	0.158	0.033	
	Compatibility * University Age → Big data adoption		
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	0.036	0.335	

6.1.4 IT Infrastructure

The study found that IT Infrastructure did not obtain accepted thresholds in the measurement model and structural model assessment. However, university size showed significant moderating effects between IT Infrastructure and big data adoption. The result of the measurement model and structural model is presented in Table 6.4. Surprisingly, the finding from data analysis shows an insignificant relationship between the IT infrastructure and big data adoption. However, this result is consistent with the study conducted by (Lai, Sun, & Ren, 2018).

A threat targets a weakness in a network or IT infrastructure that could put data or an institution at risk (Lai, Sun, & Ren, 2018). The insignificant result is because the institution's current IT infrastructure was robust and posed no threat or obstacle to the adoption of big data. The institution's IT infrastructure aids in enhancing

cross-functional institutional procedures, reducing cycle times, and developing, novel opportunities.

The current IT infrastructure for the institution has been deployed successfully and is free from connection, productivity, and security problems, including system outages and breaches. Overall, whether or not big data adoption occurs can depend on having a properly built infrastructure. So, this result indicates that the institution's IT infrastructure is the latest, and no hardware change is needed for adoption. Gender has been identified as a key aspect in describing individual interactions towards technological adoption. The demographic results of this study indicated that male respondents were dominant. Males are more influenced by their attitude to new technology than females are, but they are generally less concerned about IT infrastructure when adopting new technology (Venkatesh et al., 2020).

This hypothesis may be rejected as the majority of respondents were male.

Moreover, this study did not support the moderating effect between university age and IT infrastructure. However, it discovered a significant moderating effect between university size and IT infrastructure. Indeed, the enormous number of employees is important in enhancing the overall infrastructure.

Table 6.4: IT Infrastructure Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
	0.89	0.93	0.76
Discriminant Validity			
	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.89 0.79 0.90 0.88	0.87	0.66
IT Infrastructure → Big data adoption			
Structural Model Results	Path Co-efficient (β -value)		P-Value
	0.028		0.346
IT Infrastructure * University Size and University Age → Big data adoption			
	Path Co-efficient (β -value)		P-Value
	0.155 -0.217		0.029 0.005

6.2 Organization Factors and Hypotheses

The results of the organization factors were significant and influenced big data adoption. The results indicated that three direct hypotheses have an acceptable p-value. However, no significant moderating effects were found.

6.2.1 Top Management Support

The study found that top management support obtained accepted thresholds in a measurement model and structural model assessment. The result of the measurement model and structural model is presented in Table 6.5. The results also highlighted that top management support was the second most significant factor. It plays a vital role in the adoption of big data. This result is correlated with previous studies (Verma & Bhattacharyya, 2017; Yadegaridehkordi et al., 2020; Qasem et

al., 2020). The result of this study shows a considerable positive relationship between top management support and big data adoption. Therefore, the adoption of innovative technology is an important decision and can't be taken without top management support (Nguyen & Petersen, 2017).

Table 6.5: Top Management Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
	0.95	0.96	0.87
Discriminant Validity			
	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.97	0.93	0.47
	0.91		
	0.94		
	0.91		
Top Management Support → Big data adoption			
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	0.282	0.000	

6.2.2 Financial Resources

The study found that financial resources obtained acceptable thresholds in the measurement model and structural model assessment. The result of the measurement model and structural model is presented in Table 6.6. Concerning financial resources, this study showed the positive influence of financial resources on big data adoption. This result is supported by previous studies (Park et al., 2015; Lai et al., 2018; Yadegaridehkordi et al., 2020). However, university size has no effect on the link between financial resources and big data adoption since the funding of institutions is not dependent upon the number of employees.

Table 6.6: Financial Resources Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
	0.92	0.94	0.80
Discriminant Validity			
Structural Model Results	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.89	0.90	0.71
	0.85		
	0.88		
	0.92		
Financial Resources → Big data adoption			
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	0.171	0.009	
	Financial Resources * University Size → Big data adoption		
	Path Co-efficient (β -value)	P-Value	
	-0.171	0.009	

6.2.3 Human Expertise and Skills

The study found that human expertise and skills obtained acceptable thresholds in a measurement model and structural model assessment. The results of the measurement model and structural model are presented in Table 6.7. According to the findings, human expertise and skills are important determinants of big data adoption. It is an important factor that eases the big data adoption process (Sun et al., 2018). Therefore, insufficient human expertise and skills can lead to deferment of adoption decisions. However, this study discovered that the age of the university did not reinforce the relationship between human expertise and skills and big data adoption. A possible clarification for this result is that human expertise and skills are not based on the institute's year of existence. Expertise and skills refer to a higher level of knowledge about a specific field that is usually acquired or learned. It entails substantial, explicit, and persistent efforts from the learner's end.

Table 6.7: Human Expertise and Skills Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
	0.84	0.89	0.67
Discriminant Validity			
Structural Model Results	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.79	0.82	0.78
	0.88		
	0.85		
	0.75		
Human Expertise and Skills → Big data adoption			
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	0.233	0.000	
Human Expertise and Skills * University Age → Big data adoption			
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	-0.036	0.341	

6.3 Environmental Factors and Hypotheses

The results of the environmental factors were significant and influenced big data adoption. The results indicated that three direct hypotheses have an acceptable p-value. It has been found that two moderating effects were significant. The university age strengthens the relationship between security and privacy concerns and big data adoption. Similarly, university age strengthens the relationship between government policies and big data adoption. However, there were no moderating effects of university age between competitive pressure and big data adoption.

6.3.1 Competitive Pressure

The study found that competitive pressure obtained acceptable thresholds in the measurement model and structural model assessment. The result of the measurement model and structural model is presented in Table 6.8. The result of this study indicated that competitive pressure has a significant relationship with big data adoption. This result is supported by previous adoption research (Yadegaridehkordi et al., 2018; Tarhini et al., 2018). Universities can gain an advantage over other universities because of pressure and confrontation. Competitive pressure is also helpful as universities increase their technological standards to overcome management-related issues. This study's results showed that university age did not strengthen the relationship between competitive pressure and big data adoption. Extant literature shows that technological advancement helps in managing competitive pressure. However, the oldest existing universities with no technological advancement might not be able to manage competitive pressure.

Table 6.8: Competitive Pressure Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
	0.84	0.89	0.68
Discriminant Validity			
Structural Model Results	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.83	0.83	0.39
	0.89		
	0.85		
	0.71		
Competitive Pressure → Big data adoption			
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	0.124	0.016	
	Competitive Pressure * University Age → Big data adoption		
	Path Co-efficient (β -value)	P-Value	
	0.032	0.267	

6.3.2 Security and Privacy

The study found that security and privacy obtained acceptable thresholds in the measurement model and structural model assessment. The result of the measurement model and structural model is presented in Table 6.9. In this study, security and privacy concerns were the most significant factor that showed a negative influence on big data adoption. This result is supported by (Sabi et al., 2017; Sun, Cegielski, Jia, & Hall, 2018; Qasem et al., 2020). This implies that security and privacy concerns are more challenging in the big data adoption decision stage. The findings suggest that security and privacy concerns affect big data adoption. Therefore, it is imperative to ensure the privacy and security factor that dissuades the adoption process. Security and privacy measures become

stronger and more protective over time. Similarly, in this study, the age of the university confirms the relationship between security and privacy concerns of big data adoption.

Table 6.9: Security and Privacy Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
	0.89	0.93	0.76
Discriminant Validity			
Structural Model Results	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.87 0.85 0.88 0.88	0.87	0.26
	Security & Privacy → Big data adoption		
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	-0.359	0.000	
	Security & Privacy * University Age → Big data adoption		
Structural Model Results	Path Co-efficient (β -value)	P-Value	
	0.194	0.015	

6.3.3 Government Policies

The study found that government policies obtained acceptable thresholds in the measurement model and structural model assessment. The result of the measurement model and structural model is presented in Table 6.10. Government policies can encourage or discourage the decision of technology adoption (Sun, Cegielski, Jia, & Hall, 2018). In this study, government policies are also having a positive impact on big data adoption. This analysis result reveals that government

support and regulatory bodies are necessary for big data adoption. Similarly, the age of the university can further strengthen the relationship between government policies and big data adoption. As the age of the university increases, its reliability and reputation also increase. Therefore, government policies are more supportive of reputed institutions (Williamson, 2017).

Table 6.10: Government Policies Results

Measurement Model Results	Convergent Validity		
	Cronbach's Alpha	Composite Reliability	Average Extracted Variance (AVE)
	0.90	0.93	0.76
Discriminant Validity			
	Cross Loadings	Fornell-Larcker Criterion	Heterotrait-Monotrait Ratio (HTMT)
	0.91 0.92 0.85 0.80	0.87	0.37
Government Policies → Big data adoption			
Structural Model Results	Path Co-efficient (β -- value)	P-Value	
	0.158	0.006	
Government Policies * University Age → Big data adoption			
	Path Co-efficient (β -- value)	P-Value	
	0.113	0.014	

6.4 R² Value

The R² value of this study was 0.689. The integrity of this study model has been compared with other big data adoption studies. It has been found that this study model has exceeded it all with a significant R² value. It has been found that in previous studies, the R² results were less than in this study. Yadegaridehkordi et al. (2020) conducted a study in the big data adoption domain. In that study, the R²

value was 0.483. Similarly, Lai, Sun, and Ren (2018) conducted a study in the domain of big data adoption. In that research, the R^2 value was 0.683. However, in this study, the R^2 value was 0.689. This indicated that it had 68.9 percent integrity.

6.5 Summary

This chapter discusses the results of this study. The technology, organization, and environmental factors and hypothesized results were discussed. The results of this study showed correspondence with the results of previous big data adoption studies. Several extant studies have discussed the significance of technology, organization, and environmental related factors that support the findings of this study. The contradictory results were also described. Lastly, this chapter compares the R^2 value of this study model with other big data adoption studies models.

CHAPTER 7: CONCLUSION

7.1 Introduction

This chapter presents the conclusion of this study. In the first section, the research accomplishments related to each research objective are discussed. Next, a set of guidelines has been developed based on the findings. This section is followed by the contributions and significance of this study. The last section highlights the limitations and future research directions.

7.2 Research Accomplishments

This research aims to identify the factors that affect big data adoption in the higher education sector and develop a theoretical model for big data adoption in the higher education sector. This study endeavoured to respond to the research questions by accomplishing the following research objectives:

7.2.1 Research Objective 1: To investigate the state of the art of big data adoption.

Research question 1 (RQ1) is “What is the state of the art of big data adoption?” RQ1 is used to address the above-mentioned research objective. To investigate the state of the art of big data adoption, a comprehensive literature review was conducted to examine the current state of literature. The aim of the review was to provide a comprehensive overview of big data adoption and exiting studies. This review helped to identify the research gap, research problem, and scope of this study. The review study finds the gaps and challenges within the current research about big data adoption.

The findings of this review provided the answer to the first research question as well. Through the findings of this review study, it can be concluded that TOE and DOI were the most-used models in the big data adoption realm. TOE and DOI are highly viable in reducing technology-related challenges. Therefore, it can be used to amend the organizational structure.

This review study also highlighted that data was mainly collected from IT managers, service providers, and management. It has been found that big data adoption has already gained tremendous attention from executives in various fields. The adoption of big data is profoundly beneficial in different sectors. However, it has yet to be explored in the educational sector, where a large amount of academic data is being produced. This research objective finding has been presented in Chapter (Section 2.5).

7.2.2 Research Objective 2: To identify the factors that influence big data adoption in the higher education sector.

The research question pertaining to the second objective is RQ2 “What are the factors that influence big data adoption in the higher education sector?” In order to achieve the second research objective, a total of ten constructs were extracted from the big data adoption-related studies and matched with the scope of this study. It has been found that the theoretical model comprises many factors that can decrease the reliability and validity of the study. Therefore, all factors cannot be used. In this study, factors were selected through a comprehensive review of the big data adoption studies. The most used factors that matched the scope of this study (managerial side) were selected and summarized. Extant literature highlights their significance in adoption in the higher education context.

The findings of the comprehensive review provided the answer to the second research question as well. A total of ten constructs were extracted from the big data adoption literature and that matched the scope of this study. In Technology (relative advantage, complexity, compatibility, IT infrastructure), Organization perceptive (top management support, financial resources, human expertise and skills) and Environmental context (competitive pressure, security and privacy concerns, government policies). To measure the change effect of the construct systematically, the university age and university size were used as moderators. The detailed finding of this objective has been discussed in Chapter 4 (Section 4.2.2 and 4.2.3).

7.2.3 Research Objective 3: To develop a theoretical model for big data adoption in higher education institution.

In this context, the question in relation to the third objective is RQ3 “How to develop a theoretical model for big data adoption in the higher education institution?” To develop a theoretical model, TOE and DOI were selected as theoretical bases, and hypotheses were developed based on literature. This helps to develop a theoretical model. To develop the questionnaire, this study follows Malhotra (2010) questionnaire design process. The scale measurement of each item was adapted from extant research. The questionnaire consisted of different sections. The first section is based on demographic questions. This section consisted of five categories: Gender, Age, Role, Experience, and Campus Age. The second section of the questionnaire was based on the research model constructs. This section was further categorized into four subsections, namely, big data adoption, Technology, Organization, and Environment. For each construct, relative questions were adapted from literature and modified according to the scope

of this study. Content validity was used to ascertain the simplicity and relevancy of a designed instrument. In this study, the content validity of the questionnaire was accomplished by experts in this particular field. The questionnaire's content was revised further in light of the expert's suggestions. All experts were selected based on their expertise (Chapter 3).

A draft of questionnaire items was sent to experts. The proposed theoretical model and hypotheses were also enclosed with questionnaires to get a comprehensible view of the relevancy of items with constructs. The five experts reviewed the questionnaire and gave their opinion. Experts were asked to review the draft and evaluate each item based on two criteria, namely relevancy and simplicity. The experts were also asked to suggest revisions in the item if needed. In this study, content validity values in terms of simplicity and reliability were in the acceptable range Chapter 3 (Section 3.6.3). The content validity index helped to develop the questionnaire. The questionnaire was also tested through a pilot study (Chapters 3 - Section 3.8). The pilot study helped to confirm the preliminary reliability and validity of the questionnaire. This research objective finding has been presented in Chapter 4 (Section 4.2).

7.2.4 Research Objective 4: To validate a theoretical model for big data adoption in the higher education institution of Pakistan.

The research question pertaining to the fourth objective is RQ4 “How to validate a theoretical model for big data adoption in the HEI of Pakistan.” In this study, to validate a theoretical model, data was collected from the managerial side of VU campuses through an online quantitative survey. The questionnaire was created using a Google Form, and the generated link was emailed to the respective respondents. A total of 195 responses were included in this study. To ensure the

adequacy of the sample size, the Hair et al. (2016) rule of sample size and G-power was applied.

The model was analyzed through the measurement model (outer model) and structural model (inner model). The measurement model confirmed the construct's reliability and validity. The construct reliability was ascertained through Cronbach alpha, composite reliability and factor loading. Construct validity was achieved through convergent validity and discriminant validity. The convergent validity was ascertained through the average variance extracted. The discriminant validity was analyzed through the Fornell and Lacker criterion, cross-loading and heterotrait-monotrait. The inner model helps to test the hypothesis. The bootstrapping process was performed to test the hypothesis that is based on the direct and moderating effects. In the inner model, measurement values of path coefficient, t-values, and p-values were analyzed.

The findings of this objective provided the answer to the fourth research question. The direct association (technology, organization and environment factors) and moderating effects (indirect) (university age and university size) relationships were analyzed. The findings concluded that nine out of ten direct effects were significant. However, three out of nine moderator's effects are considerable.

The findings of this study indicated that, in total, twelve out of nineteen hypotheses were significant. Relative advantage, complexity, compatibility, top management support, financial resources, human expertise and skills, competitive pressure, security and privacy, and government policies were significant determinants of big data adoption. This research objective finding has been presented in Chapter 5 (Section 5.3).

7.3 Guidelines for Big Data Adoption based on the Findings

Based on the findings, this study provided guidelines for big data adoption in the higher education sector, as shown in Figure 7.1

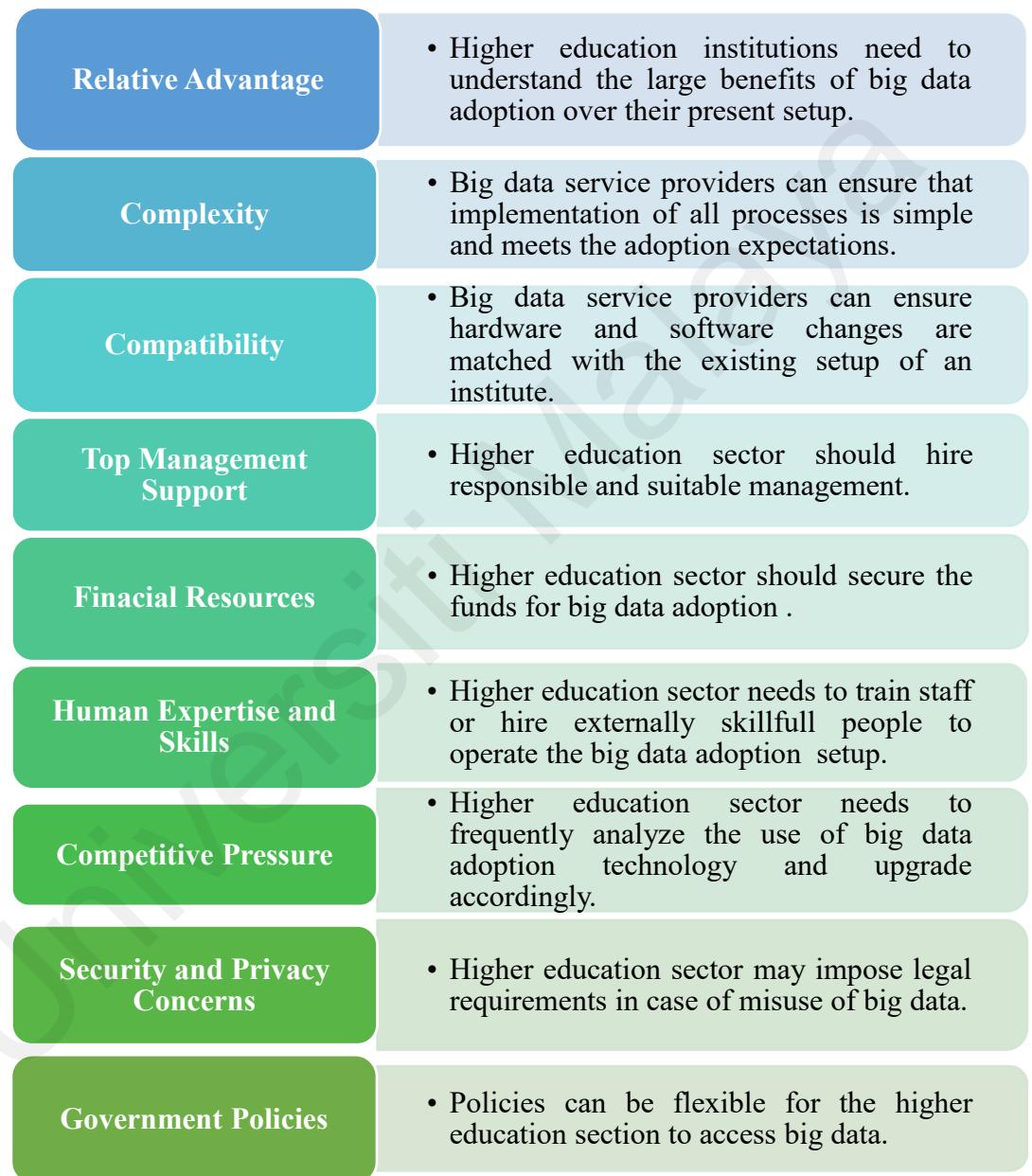


Figure 7.1: Guidelines for the Big Data Adoption based on Finding

a. Relative Advantage

It is recommended that educational institutions fully assess the existing services and analyze the future needs. Big data adoption can be helpful for institutions to cater to future needs and solve multifarious issues. Institutions can compare the level of distinction and benefits of their current services.

b. Complexity

Big data setup should be easy to adopt for the higher education sector (Figure 7.1). The adoption process should be certain and safe in terms of its success and performance. Big data service providers should ensure that all processes are simple to implement, meet adoption expectations, and achieve the desired results. Then, it should be easier for administrators to actually use the big data adoption.

c. Compatibility

The big data adoption process should be compatible with the existing setup of the higher education sector. The big data service providers should make sure that hardware and software changes need to be compatible with the existing setup of institutions. Big data service providers should also ensure that existing operating systems are compatible with newly integrated software.

d. Top Management Support

An important step of big data adoption is the training or hiring of responsible management. Therefore, the need for suitable managers that are aware of the overall big data adoption context is necessary. The top management needs to develop an overall strategy and plan, monitor the implementation and technical

details, follow the timelines, and handle possible issues. Thus, the responsibility of managers should be clearly set up for big data adoption with certainty.

e. *Financial Resources*

Financial resources are an important aspect of big data adoption. Therefore, institutions need to secure the essential funds for big data adoption. There are lots of options available that can be considered for adopting new technology. However, it is necessary to prioritize the opportunities and select the needed and affordable options based on available funding.

Eventually, the use of big data adoption leads to improvement in overall setup and reduces the cost in the long term.

f. *Human Expertise and Skills*

The higher education sector needs trained and skilful people to operate setups for big data adoption. The big data service providers need to train institutional staff to handle the setup after adoption. Additionally, institutions can hire permanent trained staff or contractors according to their setup and needs.

g. *Competitive Pressure*

The higher education sector should frequently analyze the use of technology to decide whether they need or upgrade technology to improve the setup and remain competitive with others. Big data should be properly adopted to maintain the pressure on opponents.

h. Security and Privacy Concerns

Institutions can prevent unauthorized access to big data. Data access can be protected through appropriate and standard passwords. Therefore, passwords should be based on several layers. The password can be set up before booting up.

The protection should be against computer viruses, and spy's to secure sensitive information. The system should not allow the user to access all the data. The log-in and password conditions need to be implemented for limited users.

Institutions should impose legal requirements in the case of misuse of data. It's easier for intruders to misuse the data that has remote access. The data needs to be secure on centralized servers rather than on multiple hard drives. A network risk assessment should be checked.

i. Government Policies

Government policies should be flexible and easy for the higher education sector to access data. Institutions should clearly describe what information is publicly available and ensure that they follow government advice to protect the sensitive and personal information of users.

7.4 Contribution of the Study

This study has several contributions to theory, and practical contributions for stakeholders and other researchers.

- A systematic literature review was conducted to answer questions about the state of the art in big data adoption (Baig et al., 2019). It contributed to other researchers about the state of big data adoption. Researchers can

understand the level of development in the big data adoption context and can extend it further.

- The theoretical contribution of this study is the factors that affect big data adoption and the big data adoption model in higher education in Pakistan. The researchers can use this model in other countries and educational levels.
- This study used TOE and DOI. The assimilation of TOE and DOI is another significant contribution. Assimilation models can be used by researchers in other technology adoption contexts.
- Based on findings, this study proposed the guidelines for big data adoption. These guidelines can be helpful for stakeholders as a practical contribution. Thus, this research finding can contribute to other researchers and extends the body of knowledge.

7.5 Research Significance

The findings of this research can be significantly important for big data service providers, ministry of education in providing appropriate policies for successful big data adoption.

- The proposed model and constructs can be helpful to big data service providers in providing services based on the current situation. Big data service providers can assure security and privacy measures according to university age by removing the possible security hindrance in the big data adoption process. Similarly, big data service providers can provide the facilities based on compatibility with the existing setup and human expertise and skill. Big data service providers can provide necessary

software platforms and applications to manage complexity and upgrade the current information technology infrastructure for the smooth adoption of big data according to university size. The proposed model can help maximize their services by improving the operational efficiencies in that particular context.

- Based on the identified factors, the government can develop policies that support universities to cater to the present situation. Higher education commissions can develop universities' financial support policies to ensure technological advancement. Similarly, if universities are facing some restrictions in accessing some records, the education minister can make some relaxation policies to manage that barrier.
- Big data provides significant advantages for university administrators to manage the bi process smoothly. After big data adoption, university administrators can manage the competitive pressure and get more support from top management for further effectual changes.

7.6 Limitations

This study showed significant results for big data adoption factors related to technology, organization, and the environment. But there are some limitations.

- This study proposed a model that measures the direct associations and moderating effects among independent constructs and big data adoption but not mediating effects.
- The big data adoption decision depends on the managerial side. Therefore, this study collected data from the managerial side. This study enhances the understanding of big data adoption and the academic realm from only a managerial point of view.

- The data was collected from the higher education sector institute, VU. The proposed big data adoption model should be tested at school or college level samples to generalize results across various levels of the education sector.

7.7 Future work

There are some suggestions that may guide future studies.

- This study analyzed the adoption stage of big data. However, future research can be conducted at the post-adoption stage, where data can be collected from the end-users. The TAM is a significant individual-level theory and can be used at post-adoption stage (Baig et al., 2021).
- In this research, moderating effects were analyzed among independent and dependent factors related to technology, organization, and environment. However, the mediating role of these constructs for future research could be considered.
- This study was cross-sectional. In the future, longitudinal research is expected to compare the results of different adoption periods.

7.8 Conclusion

In this chapter, an overview of research objectives has been discussed. This study accomplished all the objectives. The chapter also presented big data adoption guidelines. The guidelines were based on the findings of this study. Moreover, this chapter reviews the contributions of this study. The state of the art in big data adoption, factors affecting big data adoption, and the proposed model can contribute to knowledge and be helpful for other researchers. Furthermore, it also demonstrates that this study is significantly important for big data service

providers, the ministry of education, and stakeholders. The limitations and possible future research directions were also discussed.

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