The copyright © of this thesis belongs to its rightful author and/or other copyright owner. Copies can be accessed and downloaded for non-commercial or learning purposes without any charge and permission. The thesis cannot be reproduced or quoted as a whole without the permission from its rightful owner. No alteration or changes in format is allowed without permission from its rightful owner.

FACTORS INFLUENCING THE INTENTION TO ADOPT BIG DATA IN SMEs: THE MODERATING ROLE OF ORGANISATIONAL INNOVATIVENESS

AHMED F.S. ABULEHIA

Universiti Utara Malaysia

DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
APRIL 2026

FACTORS INFLUENCING THE INTENTION TO ADOPT BIG DATA IN SMEs: THE MODERATING ROLE OF ORGANISATIONAL INNOVATIVENESS

By
AHMED F.S. ABULEHIA

Universiti Utara Malaysia

Thesis Submitted to
Othman Yeop Abdullah Graduate School of Business,
Universiti Utara Malaysia,
in Fulfilment of the Requirement for the Degree of Doctor of Philosophy

Othman Yeop Abdullah Graduate School of Business

Kolej Perniagaan
(College of Business)

Universiti Utara Malaysia

PERAKUAN KERJA TESIS / DISERTASI
(Certification of thesis / dissertation)

Kami, yang bertandatangan, memperakukan bahawa
(We, the undersigned, certify that)

AHMED F. S. ABULEHIA

calon untuk Ijazah
(candidate for the degree of) DOCTOR OF PHILOSOPHY (ACCOUNTING)

telah mengemukakan tesis / disertasi yang bertajuk:
(has presented his/her thesis / dissertation of the following title):

FACTORS INFLUENCING THE INTENTION TO ADOPT BIG DATA IN SMEs: THE MODERATING ROLE OF ORGANISATIONAL INNOVATIVENESS.

seperti yang tercatat di muka surat tajuk dan kulit tesis / disertasi.
(as it appears on the title page and front cover of the thesis / dissertation).

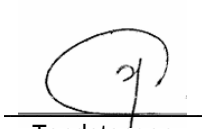
Bahawa tesis/disertasi tersebut boleh diterima dari segi bentuk serta kandungan dan meliputi bidang ilmu dengan memuaskan. Sebagaimana yang ditunjukkan oleh calon dalam ujian lisan yang diadakan pada:
19 September 2024.

(That the said thesis/dissertation is acceptable in form and content and displays a satisfactory knowledge of the field of study as demonstrated by the candidate through an oral examination held on:
19 September 2024.

Pengerusi Viva *(Chairman for Viva)*	:	Prof. Dr. Hasnah Binti Kamardin	Tandatangan *(Signature)*	
Pemeriksa Luar (*External Examiner*)	:	Assoc. Prof. Ts. Dr. **Nor'ashikin Binti Ali** (UNITEN)	Tandatangan *(Signature)*	
Pemeriksa Dalam *(Internal Examiner)*	:	Assoc. Prof. Dr. Akilah Binti Abdullah	Tandatangan *(Signature)*	

Tarikh: 19 September 2024

Nama Pelajar (*Name of Student*)	:	Ahmed F. S. Abulehia
Tajuk Tesis / Disertasi *(Title of the Thesis / Dissertation)*	:	Factors Influencing the Intention to Adopt Big Data in SMEs: The Moderating Role of Organisational Innovativeness.
Program Pengajian *(Programme of Study)*	:	Doctor of Philosophy (Accounting)
Nama Penyelia/Penyelia-penyelia *(Name of Supervisor/Supervisors)*	:	Assoc. Prof. Dr. Norhaiza Binti Khairudin
	:	Dr. Mohd Hisham Bin Mohd Sharif



Tandatangan
(Signature)



Tandatangan
(Signature)

Universiti Utara Malaysia

PERMISSION TO USE

In presenting this thesis in fulfilment of the requirements for a Post Graduate degree from the Universiti Utara Malaysia (UUM), I agree that the Library of this university may make it freely available for inspection. I further agree that permission for copying this thesis in any manner, in whole or in part, for scholarly purposes may be granted by my supervisor(s) or in their absence, by the Dean of Othman Yeop Abdullah Graduate School of Business where I did my thesis. It is understood that any copying or publication or use of this thesis or parts of it for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the UUM in any scholarly use which may be made of any material in my thesis.

Request for permission to copy or to make other use of materials in this thesis in whole or in part should be addressed to:

Dean of Othman Yeop Abdullah Graduate School of Business
Universiti Utara Malaysia
6010 UUM Sintok
Kedah Darul Aman

Universiti Utara Malaysia

ABSTRACT

Big data has gained increasing importance in both academic research and business practice due to its potential to enhance decision-making, optimise organisational processes, and generate sustainable competitive advantage. Despite these potential benefits, the adoption of big data technologies remains limited among small and medium-sized enterprises in developing economies, where resource constraints, technological uncertainty, and institutional challenges persist. While previous studies have examined big data adoption from various perspectives, empirical evidence on the combined influence of technological, organisational, and environmental factors within fragile and developing contexts remains limited. This study examines the key factors influencing the intention to adopt big data among small and medium-sized enterprises in Palestine. Guided by the Technology–Organization–Environment framework and the Diffusion of Innovation theory, the study investigates the effects of technological, organisational, and environmental determinants on adoption intention, while also examining the moderating role of organisational innovativeness. A quantitative cross-sectional design was employed, and data were collected through a structured questionnaire survey. Out of 533 distributed questionnaires, 272 usable responses were analysed using Partial Least Squares Structural Equation Modelling. The results demonstrate that relative advantage, compatibility, complexity, trialability, observability, top management support, external vendor support, and government support have significant effects on the intention to adopt big data. In contrast, organisational readiness and competitive pressure do not exhibit significant direct effects. Furthermore, organisational innovativeness moderates the relationships between relative advantage, organisational readiness, competitive pressure, and adoption intention. The findings provide valuable insights for small and medium-sized enterprises, policymakers, and technology providers by identifying critical drivers that facilitate big data adoption in developing economies. This study contributes to the big data adoption literature by extending the application of the Technology–Organization–Environment framework and Diffusion of Innovation theory to an underexplored context and by highlighting the contingent role of organisational innovativeness in shaping adoption decisions.

Keywords: Big data adoption, Adoption intentions, Technological factors, Organisational factors, Environmental factors.

ABSTRAK

Data raya semakin mendapat perhatian dalam penyelidikan akademik dan amalan perniagaan kerana potensinya untuk meningkatkan kualiti pembuatan keputusan, mengoptimumkan proses organisasi, serta mewujudkan kelebihan daya saing yang mampan. Walaupun manfaatnya semakin diiktiraf, penerimaan teknologi data raya dalam kalangan perusahaan kecil dan sederhana di ekonomi membangun masih terhad akibat kekangan sumber, ketidakpastian teknologi, dan cabaran institusi. Walaupun kajian terdahulu telah meneliti penerimaan data raya daripada pelbagai perspektif, bukti empirikal mengenai pengaruh gabungan faktor teknologi, organisasi, dan persekitaran dalam konteks ekonomi rapuh dan membangun masih terhad. Kajian ini meneliti faktor utama yang mempengaruhi niat penerimaan data raya dalam kalangan perusahaan kecil dan sederhana di Palestin. Berpandukan Kerangka Teknologi–Organisasi–Persekitaran serta Teori Difusi Inovasi, kajian ini menyiasat kesan penentu teknologi, organisasi, dan persekitaran terhadap niat penerimaan, di samping menilai peranan pemoderatan keinovatifan organisasi. Kajian ini menggunakan reka bentuk kuantitatif keratan rentas, dan data dikumpulkan melalui tinjauan soal selidik berstruktur. Daripada 533 soal selidik yang diedarkan, sebanyak 272 respons telah dianalisis menggunakan Pemodelan Persamaan Berstruktur Kuasa Dua Terkecil Separa. Dapatan kajian menunjukkan bahawa kelebihan relatif, keserasian, kerumitan, kebolehcubaan, kebolehpemerhatian, sokongan pengurusan atasan, sokongan vendor luaran, serta sokongan kerajaan mempunyai kesan yang signifikan terhadap niat penerimaan data raya. Sebaliknya, kesediaan organisasi dan tekanan persaingan tidak menunjukkan kesan langsung yang signifikan. Selain itu, keinovatifan organisasi didapati memoderasi hubungan antara kelebihan relatif, kesediaan organisasi, tekanan persaingan, dan niat penerimaan. Secara keseluruhannya, dapatan kajian ini memberikan pandangan yang bermakna kepada perusahaan kecil dan sederhana, penggubal dasar, serta penyedia teknologi dengan mengenal pasti pemacu utama yang memudahcara penerimaan data raya dalam ekonomi membangun. Kajian ini turut menyumbang kepada literatur penerimaan data raya dengan memperluas aplikasi Kerangka Teknologi–Organisasi–Persekitaran dan Teori Difusi Inovasi dalam konteks yang masih kurang diterokai, di samping menonjolkan peranan bersyarat keinovatifan organisasi dalam membentuk keputusan penerimaan teknologi.

Kata kunci: Penerimaan data raya, Niat penerimaan, Faktor teknologi, Faktor organisasi, Faktor persekitaran.

ACKNOWLEDGEMENT

First and foremost, all thanks and praise are due to Almighty Allah, the Merciful, the All-Hearing, and the All-Seeing, who has answered our prayers in attaining this noble quest. Alhamdulillah WA Lillahil Hamd. I am indebted to my supervisors, Dr. Norhaiza Khairudin and Dr. Mohd Hisham Mohd Sharif, for their constructive contributions, criticisms, untiring support, guidance, and patience throughout the course of my study. Your understanding, scholarly advice, weekly submissions, and numerous presentations have indeed shaped me into a better and more equipped scholar. For this, I will remain eternally grateful.

I am also immensely thankful to my father "Farid Abulehia", who has been my foremost inspiration. His unwavering support and encouragement have played a pivotal role in shaping my journey towards knowledge and meaningful accomplishments during my doctoral pursuit. His guidance in the pursuit of wisdom and productive endeavors has been a driving force in my academic and personal growth.

I would also like to wholeheartedly thank my beloved mother "Kamlah Abushab", whose unending encouragement, support, and prayers carried me through tough times and kept me motivated to achieve what once seemed unattainable. She has consistently been my anchor and guide in both good and bad times.

My heartfelt gratitude and unending appreciation extend to my soulmate and beloved wife "Reem Al-Braim". Thank you for being an integral part of my life and my source of strength, for sharing my joys, sorrows, fears, challenges, and achievements. May Allah bless our home with abundant Baraka. To my children, "Aya, Farid, Feras, and Mohamad", you are my life and the driving force behind my journey. I am grateful to Allah for you and pray that the mutual sacrifices we've made continue to yield fruitful results. May He grant us a long, happy, and prosperous life.

A very special and warm thank you to my brothers "Salem, Mohamed, Abdullah, Mostafa, Mahmoud, Ammar", sisters "Hala, Heba, Heam", father-in-law, mother-in-law, and all family members. Your sacrifices, patience, love, support, and encouragement have been instrumental in guiding and spiritually uplifting me throughout my life.

To Salem and Abdullah, I had dedicated this thesis to you once while you were alive, and now I dedicate it to you again as martyrs, after you were killed during the Al-Aqsa Flood war following the targeting by the Israeli occupation. May Allah grant you the highest ranks in Jannah.

I would also like to express my gratitude to my friends and colleagues who have contributed in various ways to help me successfully complete this work. Their assistance and encouragement have been invaluable.

Above all, I dedicate this work to my beloved Palestine, to the martyrs, the wounded, the prisoners, and all the resilient people of Palestine, and to Jerusalem, the eternal capital of Palestine.

LIST OF PUBLICATION

1. Abulehia, A. F. S., Khairudin, N., & Sharif, M. H. M. (2023). Factors Influencing the Intention to Adopt Big Data in Small Medium Enterprises. In M. Al-Emran, M. A. Al-Sharafi, & K. Shaalan (Eds.), Lecture Notes in Networks and Systems: Vol. 550 LNNS (pp. 137–149). Springer International Publishing. https://doi.org/10.1007/978-3-031-16865-9_12

2. Abulehia, A. F. S., Khairudin, N., & Mohd Sharif, M. H. (2025). Determinants of intention to adopt big data in Palestinian SMEs: Organizational innovativeness as a moderator. Journal of Advanced Research in Applied Sciences and Engineering Technology, 65(1), 226–247. https://doi.org/10.37934/araset.65.1.226247

Universiti Utara Malaysia

TABLE OF CONTENTS

PERMISSION TO USE iii
ABSTRACT iv
ABSTRAK v
ACKNOWLEDGEMENT v
LIST OF PUBLICATION vii
TABLE OF CONTENTS viii
LIST OF TABLES xi
LIST OF FIGURES xii
LIST OF ABBREVIATIONS xiii

CHAPTER 1 INTRODUCTION 1
1.1 Background of the Study 1
1.2 Problem Statement 7
1.3 Research Questions 9
1.4 Research Objectives 10
1.5 Scope of the Study 11
1.6 Significance of the Study 12
1.7 Definition of Key Terms 15
1.8 Thesis Structure 16

CHAPTER 2 LITERATURE REVIEW 18
2.1 Introduction 18
2.2 Big Data Definition 18
2.3 Differences Between Big Data And Traditional Data 20
2.4 Big Data Applications 21
2.5 Big Data for SMEs: Benefits and Challenges 22
2.6 Definition and Role of SMEs 24
2.7 Intention to Adopt Big Data 25
2.8 Technology–Organization– Environment (TOE) 26
2.8.1 Technological Factors 28
2.8.2 Organisational Factors 35
2.8.3 Environmental Factors 39
2.9 Organisational Innovativeness 44

Universiti Utara Malaysia

2.10 Deployment Theories 47
2.10.1 The Theory of Reasoned Action (TRA) 48
2.10.2 The Theory of Planned Behavior (TPB) 50
2.10.3 The Technology Acceptance Model (TAM) 52
2.10.4 The Unified Theory of Acceptance and Use of Technology (UTAUT) 54
2.10.5 Diffusion of Innovation Theory (DOI) 56
2.10.6 The Technology-Organization-Environment (TOE) 58
2.10.7 Integration of Innovation Theory (DOI) and TOE Frameworks 62
2.11 Chapter Summary 63

CHAPTER 3 METHODOLOGY 66
3.1 Introduction 66
3.2 Theoretical Framework 67
3.3 Hypotheses Development 69
3.3.1 Technological Factors 69
3.3.2 Organisational Factors 74
3.3.3 Environmental Factors 77
3.3.4 Moderator Role of Organisational Innovativeness 80
3.4 Research Design 85
3.4.1 Nature of the study 87
3.4.2 Unit of Analysis 87
3.4.3 Research Approach 88
3.4.4 Population and Sample Frame 90
3.5 Measurement and Operationalization of Variables 96
3.5.1 Measurement of Relative Advantage 96
3.5.2 Measurement of Compatibility 98
3.5.3 Measurement of Complexity 99
3.5.4 Measurement of Trialability 101
3.5.5 Measurement of Observability 102
3.5.6 Measurement of Top Management Support 103
3.5.7 Measurement of Organisational Readiness 104
3.5.8 Measurement of Competitive Pressure 106
3.5.9 Measurement of External Support from Vendors 107
3.5.10 Measurement of Governmental Support 108
3.5.11 Measurement of Organisational Innovativeness 109

Universiti Utara Malaysia

3.5.12 Measurement of Intention to Adopt Big Data 111
3.6 Questionnaire Design 112
3.7 Data Analysis Techniques 114
3.8 Chapter Summary 116

CHAPTER 4 RESULT OF STUDY 117
4.1 Introduction 117
4.2 Data Screening 117
4.2.1 Normality Test 118
4.3 Common Method Bias 119
4.4 Demographic Analysis 119
4.4.1 Companies Profile 119
4.4.2 Respondents' Profile 122
4.5 Results of Main Analyses 124
4.6 SUMMARY 139

CHAPTER 5 DISCUSSION, IMPLICATION AND CONCLUSION 141
5.1 Introduction 141
5.2 Recapitulation of the Study 141
5.3 Discussion of Findings 145
5.3.1 Technological Context 145
5.3.2 Organisational Context 154
5.3.3 Environmental Context 159
5.3.4 The Moderating Role of Organisational Innovativeness 166
5.4 Implications for the Study and Practice of TOE Drivers on IABD 169
5.4.1 Implications for the Body of Knowledge and Theory 170
5.4.2 Implications for Practitioners, Decision Makers 171
5.4.3 Implications for Society 172
5.5 Limitations and Future Research 173
5.6 Conclusion 175

REFERENCES 178
APPENDIX 194

Universiti Utara Malaysia

LIST OF TABLES

Table 1.1 Ranking of Palestine in ICT According (ITU) Index 3
Table 1.2 Definitions of Key Terms Used in the Study 15
Table 2.1 Typical Views of Big Data Definitions 19
Table 2.2 Differences Between Big Data and Traditional Data 20
Table 2.3 Classification of Palestinian Enterprises 25
Table 3.1 Summary Results of Establishments Census 2012, 2017 92
Table 3.2 Distribution of Operating Establishments 93
Table 3.3 Number of Operating Establishments 93
Table 3.4 Number and Percentage of SMEs in Gaza Stripe 94
Table 3.5 Measurement of Relative Advantage 98
Table 3.6 Measurement of Compatibility 99
Table 3.7 Measurement of Complexity 100
Table 3.8 Measurement of Trialability 102
Table 3.9 Measurement of Observability 103
Table 3.10 Measurement of Top Management Support 104
Table 3.11 Measurement of Organisational Readiness 105
Table 3.12 Measurement of Competitive pressure 107
Table 3.13 Measurement of External support from vendors 108
Table 3.14 Measurement of Governmental Support 109
Table 3.15 Measurement of Organisational Innovativeness 110
Table 3.16 Measurement of Intention to Adopt Big Data 112
Table 4.1 Summary on the Rate of Return Questionnaires 118
Table 4.2 Common Bias 119
Table 4.3 Summary of Companies' Profile 120
Table 4.4 Respondents' Profile 123
Table 4.5 T-test Result for Comparing Early and Late Responses. 125
Table 4.6 Descriptive Statistics. 126
Table 4.7 Correlation Matrix between Technological Factors 127
Table 4.8 Correlation Matrix between Organisational Factors 127
Table 4.9 Correlation Matrix between Environmental Factors 127
Table 4.10 Correlation Matrix between T-O-E Constructions 127
Table 4.11 Constructs Items, Indicator's Reliability, and AVE 129
Table 4.12 Discriminant Validity – Fornell-Larcker Criterion 131
Table 4.13 Discriminant Validity-Heterotrait-Monotrait (HTMT) 132
Table 4.14 VIF Values among Model Predictors 133
Table 4.15 Results of R^2 134
Table 4.16 Results of Q^2 134
Table 4.17 Result of f2 135
Table 4.18 Significance Testing Results of The Structural Model Path 136
Table 4.19 Moderating Effects of Organisational Innovativeness 137
Table 4.20 Summary of Hypotheses Testing (Main Effects Model) 140
Table 4.21 Summary of Hypotheses Testing (Moderating Effects) 140

Universiti Utara Malaysia

LIST OF FIGURES

Figure 2.1 Theory of Reasoned Action 50
Figure 2.2 Theory of Planned Behaviour 52
Figure 2.3 Technology Acceptance Model 54
Figure 2.4 UTAUT Model 55
Figure 2.5 Model of Stages in the Innovation-Decision Process 58
Figure 2.6 Technology-Organization-Environment Framework 59
Figure 2.7 Summary of Independent Variables that Influence 65
Figure 3.1 Research Process 67
Figure 3.2 Research Framework 68
Figure 3.3 Deductive and Inductive Approaches 90
Figure 4.1 Results of the First Structural Model 137
Figure 4.2 Results of the First Structural Model (After Moderation) 138

Universiti Utara Malaysia

LIST OF ABBREVIATIONS

The following abbreviations are used in this thesis:

4IR	4th Industrial Revolution
BD	Big Data
BDA	Big Data Adoption
CMPLX	Complexity
COMP	Compatibility
COMPR	Competitive Pressure
DOI	Diffusion of Innovation
EXSUPP	External Vendors Support
GOVS	Governmental Support
IABD	Intention to Adopt Big Data
ICT	Information and Communication Technology
INNOV	Organisational Innovativeness
IS	Information System
IT	Information Technology
OB	Observability
OR	Organisational readiness
PEOU	Perceived Ease of Use
PLS	Software and Analysis of Partial Least Squares
PU	Perceived Usefulness
RADV	Relative Advantage
SEM	Structural Equation Modeling
SMEs	Small and Middle-Sized Enterprises
SPSS	Statistical Package for Social Science
TAM	The Technology Acceptance Model
TMS	Top Management Support
TOE	Technology-Organization-Environment
TPB	Theory of Planned Behaviour
TR	Trialability
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology

Universiti Utara Malaysia

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

The Fourth Industrial Revolution (4IR) has transformed business environments worldwide by introducing advanced technologies such as artificial intelligence, robotics, the Internet of Things, and big data (BD). These technologies have reshaped how organisations operate, compete, and innovate in an increasingly globalized economy (Manyika et al., 2011). Among them, big data adoption (BDA) has gained particular attention because of its potential to create new business value through the use of data-driven insights. BDA enables firms to analyze vast amounts of structured and unstructured data to support decision-making, optimize processes, and enhance competitiveness (Chen et al., 2015; Davenport, 2014).

Universiti Utara Malaysia

BDA has been widely implemented across different industries in developed economies. In manufacturing, it helps firms optimize production and supply chains; in healthcare, it supports predictive diagnostics; in retail, it improves customer segmentation and personalization; and in finance, it enhances fraud detection and risk management (Gunasekaran et al., 2017; Sun et al., 2018). These benefits demonstrate why BDA is considered a core capability for innovation and sustainable growth. However, while large enterprises have embraced BD at scale, small and medium-sized enterprises (SMEs) continue to lag behind, facing numerous barriers to adoption (Organisation for Economic Co-operation and Development [OECD], 2021).

The global uptake of BDA has not been uniform. Firms in advanced economies have integrated BD into their strategic activities, supported by mature infrastructure, skilled human capital, and policy incentives (Park & Kim, 2021). By contrast, SMEs in many developing countries remain at the early stages of adoption. Key barriers include financial constraints, lack of technological readiness, insufficient expertise, and weak institutional support (Dlamini, 2024). This disparity has created a digital divide that limits SMEs' ability in developing regions to compete on equal terms with larger or foreign firms.

Research further highlights that empirical studies of BDA are concentrated in developed economies, leaving developing regions underexplored (Elmashtawy & Salaheldeen, 2023; Lutfi et al., 2022b). In India, for instance, only 15% of SMEs have adopted BD due to awareness gaps and implementation challenges (Singh et al., 2022). In Malaysia, SMEs report technological and financial limitations, while in Saudi Arabia and South Africa, lack of expertise and institutional support constrain adoption (Alshammari et al., 2021; Dlamini, 2024). Even in advanced economies like South Korea and Norway, the high cost of BDA tools and limited government incentives continue to restrict adoption (Park & Kim, 2021). These findings show that the challenges to BDA adoption are global but are especially acute in resource-constrained environments.

Palestine provides a particularly relevant context for examining BDA because of its unique structural and political conditions. Although digital transformation has been a government priority since 2005, progress has been uneven and slow. According to the International Telecommunication Union [ITU], (2017), Palestine ranked 123rd of 174

countries globally and 14th of 19 Arab states on the ICT Development Index, highlighting persistent gaps in infrastructure, connectivity, and readiness.

Table 1.1 below shows Palestine's position in ICT rankings. The ranking reflects the systemic challenges faced by Palestinian enterprises, including restricted access to advanced technologies, dependence on external approvals for telecommunication infrastructure, and limited access to high-speed internet. These constraints directly affect the readiness of SMEs to adopt BD.

Table 1.1
Ranking of Palestine in ICT According (ITU) Index

Region	Ranking
Global	123rd (out of 176)
Arab States	14th (out of 19)

Source: International Telecommunication Union [ITU] (2017).

National surveys further confirm the slow pace of adoption. The Palestinian Central Bureau of Statistics [PCBS], (2022) reported that although some enterprises had adopted technologies such as the Internet of Things (43.8%) and artificial intelligence (13.4%), systematic reporting on BDA was absent, suggesting that uptake remains minimal. These findings emphasize the importance of studying the determinants of intention to adopt big data (IABD) among Palestinian SMEs as a necessary step toward bridging the digital gap.

Globally, SMEs are acknowledged as essential contributors to growth, job creation, and innovation (Dogbe et al., 2020). They constitute more than 90% of enterprises worldwide and employ the majority of the workforce. Their capacity to embrace digital

Universiti Utara Malaysia

technologies is therefore critical to achieving inclusive and sustainable economic development (OECD, 2021).

In Palestine, SMEs are even more central to the economy. They account for approximately 95% of all enterprises and employ more than 80% of the private-sector workforce (PCBS, 2022). According to Alfoqahaa (2018), SMEs in Palestine operate in diverse sectors such as trade, manufacturing, agriculture, and services, and they contribute about 55% to national GDP. Beyond their economic role, SMEs are vital for poverty alleviation, social stability, and the development of entrepreneurial talent. However, Palestinian SMEs face additional barriers due to financial constraints, political instability, and limited access to external markets. For these reasons, empowering SMEs to adopt digital innovations like BD is vital for enhancing competitiveness and resilience.

To examine technology adoption, this study draws on the Technology–Organization–Environment (TOE) framework developed by Tornatzky and Fleischer (1990). TOE has been widely applied to study the adoption of digital innovations at the organisational level across different contexts, including cloud computing, e-commerce, and enterprise systems (Awa et al., 2016; Xu et al., 2017; Amoah et al., 2023). The framework identifies three sets of factors influencing adoption:

- Technological context: relative advantage (RADV), compatibility (COMP), complexity (CMPLX), trialability (TR), and observability (OB) (Rogers, 2003).
- Organisational context: top management support (TMS) and organisational readiness (OR) (Nam et al., 2015; Lai et al., 2018).

- Environmental context: competitive pressure (COMPR), external vendor support (EXSUPP), and governmental support (GOVS) (Zhu et al., 2006; Angwar et al., 2018).

The strength of this study lies in integrating the Diffusion of Innovation (DOI) theory with the Technology–Organization–Environment (TOE) framework. While DOI explains adoption through technological attributes such as RADV, COMP, CMPLX, TR, and OB, TOE extends this perspective by including organisational and environmental contexts such as TMS, OR, COMPR, GOVS, and EXSUPP. This integration provides a more comprehensive and nuanced understanding of BDA in SMEs, making it particularly suitable for the Palestinian context where both innovation attributes and contextual constraints interact to shape adoption decisions.

In addition to the TOE and DOI factors, this study incorporates INNOV as a moderating variable. DOI highlights that adoption is influenced by innovation characteristics such as RADV, COMP, and CMPLX, while TOE emphasizes organisational and environmental contexts. INNOV, in this sense, reflects an organisation's willingness to embrace, experiment with, and apply new ideas and technologies (Damanpour, 1991; Marcati et al., 2008). Prior studies have shown that innovative firms are more likely to adopt emerging technologies, as they are better positioned to overcome resistance to change, explore creative solutions, and adapt to dynamic environments (Lee, 2004; Alshamaila et al., 2013). By integrating TOE, DOI, and INNOV, this study develops a comprehensive framework to better explain variations in SMEs' IABD.

Universiti Utara Malaysia

The role of INNOV is especially relevant in SMEs, where the leadership style of managers or owners often determines adoption decisions (Premkumar & Roberts, 1999). Within the integrated TOE–DOI framework, INNOV acts as a moderator that can explain variations in how both innovation characteristics (RADV, COMP, CMPLX, TR, and OB) and organisational or environmental factors influence adoption. By introducing INNOV as a moderator, this study seeks to clarify inconsistent findings in prior research regarding the influence of TOE and DOI factors on IABD (Verma & Chaurasia, 2019; Park & Kim, 2021). Following the moderation logic of Baron and Kenny (1986), INNOV may strengthen or weaken the impact of technological, organisational, environmental, and innovation-related contexts on SMEs' IABD.

This background establishes the broader context for the study. While BDA has transformed industries globally, adoption remains uneven and particularly challenging for SMEs in developing economies. Palestine illustrates these challenges sharply, with SMEs playing a central role in economic development but operating under severe infrastructural and financial constraints. Building on the integrated TOE–DOI framework and incorporating INNOV as a moderator, this study aims to provide new insights into the determinants of IABD in Palestinian SMEs. The TOE framework highlights organisational and environmental readiness, while DOI emphasizes innovation attributes such as RADV, COMP, and CMPLX. By combining these perspectives and testing the moderating role of INNOV, this study contributes to both theory and practice by clarifying how SMEs in fragile economies can overcome adoption barriers and leverage BD for sustainable growth.

1.2 Problem Statement

BDA enhances business operations by enabling data-driven decision-making, boosting efficiency, competitiveness, and innovation. While large enterprises have successfully adopted BDA, SMEs face significant adoption challenges, creating a notable gap compared to larger enterprises (Lutfi et al., 2022b). Despite growing awareness of BDA's benefits, adoption rates among SMEs remain critically low, limiting their ability to leverage data for growth and sustainability.

Empirical research highlights this gap globally. In the EU and UK, only 10% of SMEs have integrated BDA, compared to higher adoption rates among large firms (OECD, 2021). Similarly, only 15% of Indian SMEs adopted BDA, citing awareness and implementation barriers as key challenges (Singh et al., 2022). This trend persists in Malaysia, Saudi Arabia, and South Africa, where SMEs face technological, financial, and expertise-related constraints (Alshammari et al., 2021; Dlamini, 2024). Even in advanced economies like South Korea and Norway, adoption remains limited due to high costs and insufficient government incentives (Park & Kim, 2021).

The adoption gap is more pronounced in developing economies, where SMEs encounter greater infrastructural and financial challenges. While developed economies have explored BDA strategies (Schüll et al., 2018), research in developing regions often focuses on broader ICT adoption rather than BDA-specific challenges (Elmashtawy & Salaheldeen, 2023; Lutfi et al., 2022b). In the Middle East, SMEs face limited digital infrastructure, skilled personnel shortages, and insufficient government support, further hindering adoption.

In Palestine, the situation is even more challenging. Ranked 123rd out of 174 countries in the ITU ICT Development Index, Palestine lags in digital transformation (ITU, 2017). Palestinian SMEs, forming the backbone of the national economy, struggle with weak infrastructure, financial constraints, and limited expertise (PCBS, 2022). Despite these challenges, empirical studies examining BDA among Palestinian SMEs remain scarce, highlighting a critical research gap.

A major limitation in existing research is the focus on firms that have already adopted BD, overlooking the intention to adopt among SMEs facing significant barriers such as financial constraints, limited expertise, and inadequate organisational readiness (Maroufkhani et al., 2020b). Understanding intention to adopt is crucial, as SMEs with strong adoption intentions are more likely to succeed if provided appropriate support.

An overlooked but critical factor is INNOV, defined as a firm's ability to embrace, experiment with, and integrate new technologies (Dremel et al., 2020). Research shows that innovative organisations are more likely to adopt emerging technologies by overcoming resistance to change and leveraging new opportunities (Verma & Bhattacharyya, 2017). In the BDA context, INNOV facilitates adoption by reducing complexity, enhancing compatibility, and fostering experimentation. However, its moderating role remains underexplored.

Existing literature using the TOE framework and DOI theory presents inconsistent findings on key adoption determinants. Some studies found strong relationships between factors like RADV, COMP, and COMPR, while others reported weak or non-significant relationships (Verma & Chaurasia, 2019; Park & Kim, 2021). According to Baron and Kenny's (1986) moderation theory, inconsistent relationships can be

Universiti Utara Malaysia

clarified by introducing a moderating variable. In this case, INNOV may strengthen or weaken the influence of TOE factors on IABD, depending on the firm's internal capabilities.

Scholars such as Park and Kim (2021) and Brock and Khan (2017) emphasize the need for further research on INNOV as a moderating factor, noting that existing studies often overlook organisational characteristics that shape SMEs' ability to navigate adoption challenges. Despite these recommendations, empirical studies exploring the interaction between INNOV and BDA determinants among SMEs remain limited.

To address these gaps, this study develops an integrated model based on the TOE and DOI frameworks to examine the factors influencing IABD among Palestinian SMEs. It further investigates the moderating role of INNOV, providing new insights into how SMEs can overcome adoption barriers. These findings inform policymakers, SME managers, and technology providers about key enablers of BDA in developing economies, contributing to the broader discourse on SME digital transformation.

Universiti Utara Malaysia

1.3 Research Questions

Based on the above-stated problems, the current study aims to extend the knowledge and understanding of the most important factors influencing the IABD among SMEs in developing economies, including Palestine. The primary research questions are as follows:

1. What is the relationship between technological factors (relative advantage, compatibility, complexity, trialability, and observability) and the intention to adopt big data among SMEs in developing economies?
2. What is the relationship between organisational factors (top management

support and organisational readiness) and the intention to adopt big data among SMEs in developing economies?

3. What is the relationship between environmental factors (competitive pressure, external vendor support, and governmental support) and the intention to adopt big data among SMEs in developing economies?
4. How does organisational innovativeness moderate the relationship between TOE factors (technological, organisational, and environmental) and the intention to adopt big data among SMEs in developing economies?

1.4 Research Objectives

The current study sets the following objectives to explore the answers to the questions mentioned above regarding the IABD among SMEs in developing economies, including Palestine:

1. To examine the relationship between technological factors (relative advantage, compatibility, complexity, trialability, and observability) and the intention to adopt big data among SMEs in developing economies.
2. To investigate the relationship between organisational factors (top management support and organisational readiness) and the intention to adopt big data among SMEs in developing economies.
3. To explore the relationship between environmental factors (competitive pressure, vendor support, and governmental support) and the intention to adopt big data among SMEs in developing economies.
4. To assess the moderating role of organisational innovativeness in the relationship between TOE factors (technological, organisational, and environmental) and the intention to adopt big data among SMEs in developing

Universiti Utara Malaysia

economies.

1.5 Scope of the Study

This study investigates the factors influencing IABD among SMEs in developing economies, with a specific focus on Palestinian SMEs. The study employs the TOE and DOI frameworks to explore how technological, organisational, and environmental factors affect SMEs' IABD, while assessing the moderating role of INNOV. The study targets SMEs operating in Palestine, specifically within the Gaza Strip, across its five governorates: North Gaza, Gaza City, Deir al-Balah, Khan Yunis, and Rafah. The West Bank was excluded from the study due to the geographical separation and communication challenges caused by the Israeli occupation.

The research covers SMEs from the main sectors defined by the Palestinian Central Bureau of Statistics (PCBS), under which all other sub-sectors are classified. These primary sectors include Agriculture, Manufacturing, Construction, Wholesale and Retail Trade, Transportation and Storage, Information and Communications, and Services and Other Branches. This classification ensures comprehensive sectoral coverage, thereby providing a holistic understanding of the factors influencing IABD across all SME sectors, serving as a comprehensive model applicable to SMEs in other developing economies.

The population under investigation includes owners, managers, and key decision-makers within SMEs, as they are directly responsible for organisational decisions regarding technology adoption. Lower-level employees, external consultants, and stakeholders who do not influence adoption decisions are excluded from the study.

The thematic focus of the study is on IABD rather than actual adoption, allowing for

Universiti Utara Malaysia

the identification of barriers and enablers affecting SMEs' decision-making process before adoption occurs. By utilizing the TOE and DOI frameworks, the study examines how technological, organisational, and environmental drivers, alongside INNOV, shape SMEs' readiness for IABD. The study excludes large enterprises (20 or more employees), non-profit organisations, and those outside the defined geographical regions. This defined scope ensures a focused and contextually relevant investigation that aligns with the study's objectives and problem statement.

1.6 Significance of the Study

This study holds significant value across multiple domains, including academic contributions, practical implications for decision-makers, and broader societal benefits. By examining the factors influencing IABD among SMEs using the TOE and DOI frameworks, the study offers insights into overcoming adoption challenges and enhancing digital transformation in developing economies. Additionally, the inclusion of INNOV as a moderating variable addresses an important gap in literature, where most existing studies have primarily focused on direct relationships between TOE factors and IABD.

The study contributes to the existing literature by addressing gaps related to IABD among SMEs, particularly in developing economies like Palestine. While previous research primarily focused on BDA in larger enterprises, this study shifts the focus to the intention to adopt, which is a critical yet underexplored phase for SMEs. By integrating the TOE and DOI frameworks with the moderating role of INNOV, the study provides a more comprehensive understanding of how technological, organisational, and environmental factors shape SMEs' readiness for BDA.

While many previous studies have examined direct relationships between adoption factors and adoption decisions, this study uniquely explores how INNOV moderates these relationships. This perspective allows for a deeper understanding of how SMEs with greater innovativeness can better overcome perceived adoption barriers, adapt to new technologies, and foster a culture of experimentation and technological readiness. The findings enrich theoretical discussions by offering empirical evidence from a developing economy context, thus advancing the understanding of technology adoption dynamics in resource-constrained environments.

For decision-makers within SMEs, the study offers practical insights into the key drivers and barriers affecting their intention to adopt big data. The identified factors RADV, COMP, CMPLX, TR, OB, TMS, OR, COMPR, EXSUPP, and GOVS highlight areas where businesses can focus their efforts to facilitate adoption. Additionally, understanding the moderating role of INNOV empowers decision-makers to foster a culture of innovation, ensuring that their organisations are better prepared to embrace digital transformation. INNOV enhances compatibility with new technologies, reduces uncertainty, and encourages SMEs to experiment with digital solutions, making the transition to BDA more feasible. These insights can guide strategic planning, resource allocation, and capacity-building initiatives within SMEs, helping businesses align their internal capabilities with external technological opportunities.

On a broader societal level, promoting BDA among SMEs can lead to increased business efficiency, job creation, and economic growth. As SMEs represent a significant portion of the economy in developing countries, their ability to leverage BD can enhance competitiveness, drive innovation, and contribute to sustainable

development. Furthermore, the study's findings can inform policymakers, industry associations, and support organisations, such as the Palestinian Information Technology Association (PITA) and the Ministry of Communications and Information Technology (MCIT), in designing targeted programs, incentives, and infrastructure improvements to support SMEs in their digital journey. This alignment between technological advancement and socioeconomic development underscores the broader relevance of the study's outcomes.

Universiti Utara Malaysia

1.7 Definition of Key Terms

To ensure conceptual clarity and consistency throughout this study, the key terms used in the research are defined in Table 1.2. These definitions are drawn from established literature and reflect how each concept is operationalized within the context of this study.

Table 1.2
Definitions of Key Terms Used in the Study

Item	Definition
Big Data (BD)	Extremely large datasets characterized by high volume, velocity, and variety, requiring advanced techniques for analysis (Chen et al., 2014).
Intention to Adopt Big Data (IABD)	The degree to which decision-makers in SMEs are willing and prepared to implement big data solutions (Venkatesh et al., 2003).
Technology-Organization-Environment (TOE) Framework	A framework explaining how technological, organisational, and environmental contexts influence innovation adoption (Tornatzky & Fleischer, 1990).
Diffusion of Innovation (DOI) Theory	Theory describing how innovations spread within a social system over time, emphasizing innovation characteristics and communication channels (Rogers, 2003).
Organisational Innovativeness (INNOV)	An SME's ability and willingness to adopt new ideas, processes, or technologies to enhance performance and competitiveness (Hult et al., 2004).
External Vendor Support (EXSUPP)	Technical assistance, training, and resources provided by vendors to facilitate big data adoption (Thong et al., 1996).
Relative Advantage (RADV)	The perceived benefits of adopting big data compared to existing practices, such as improved decision-making and efficiency (Rogers, 2003).

Universiti Utara Malaysia

Compatibility (COMP)	The degree to which big data aligns with existing values, needs, and practices within SMEs, facilitating easier adoption (Moore & Benbasat, 1991).
Competitive Pressure (COMPR)	External influence exerted by competitors, driving SMEs to adopt big data to maintain or gain a competitive edge (Oliveira & Martins, 2010).
Top Management Support (TMS)	Commitment and encouragement from senior leadership for big data adoption (Premkumar & Roberts, 1999).
Observability (OB)	The extent to which big data benefits are visible within and outside the organisation, promoting further adoption (Rogers, 2003).
Trialability (TR)	The ability of SMEs to experiment with big data solutions before full-scale adoption (Moore & Benbasat, 1991).
Governmental Support (GOVS)	Policies, funding, and initiatives provided by the government to promote big data adoption among SMEs (Baker, 2012).

1.8 Thesis Structure

Chapter 1 serve as an essential introduction to the research. Chapter 2 provides the literature review on big data and the background information on TOE factors and their relationship with the intention of adopting big data.

Chapter 3 provides the research framework and hypotheses underlying the study drawn on the TOE theory. It also explains the research methodology adopted for this study. A questionnaire survey was used for the data collection method in this study, and the intention of implementing the technique is to yield greater understanding and allow better inferences of the research findings. The quantitative approach is the dominant approach, where the research process starts with the design and development of the survey questions, followed by the administration of the survey and, finally statistical analysis. A description of the measurement of variables is included as part of the

quantitative elements.

Chapter 4 focuses on presenting and discussing the results of the quantitative analysis. The chapter presents a general background of the respondents. The quantitative analysis then proceeds with the development of summated variables using SmartPLS. The validity and reliability of the instruments were established, and path model and hypothesis tests were done for research findings.

Chapter 5 draws the general discussion on the questionnaire findings. The main findings are reviewed concerning the research questions and followed by the study's contribution. Lastly, the study's limitations are presented before suggesting avenues for future research.

Universiti Utara Malaysia

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews previous studies related to BD and SMEs to establish the foundation of the research. It begins with a general overview of BD and the global SME context before highlighting the situation of Palestinian SMEs as the study setting. The chapter then discusses the key benefits and challenges of BDA in SMEs, drawing comparisons between developed and developing economies to clarify the practical and theoretical gaps. Based on this background, the discussion moves to IABD as the core focus of the study, examining the main determinants and the moderating role of INNOV. The final part of the chapter integrates the TOE framework and the DOI theory to construct a coherent theoretical basis and develop the conceptual framework that guides this research.

Universiti Utara Malaysia

2.2 Big Data Definition

The concept of BD has been described in numerous ways, reflecting its evolution across technological and business disciplines. Scholars generally agree that BD represents data of exceptional volume, velocity, and variety, which surpass the capacity of traditional data management tools (Cooper & Mell, 2012). From a business intelligence perspective, BD enables firms to process extensive and complex datasets to extract valuable insights for strategic and operational decisions (Oliveira, Thomas, & Espadanal, 2014).

Table 2.1 presents a synthesis of representative definitions from the literature. These definitions demonstrate how researchers have conceptualized BD as both a technological capability and a strategic resource that supports analytics-driven decision-making.

Table 2.1
Typical Views of Big Data Definitions

Sources	Key viewpoints
Boubeta-Puig et al. (2014)	Big data is "an approach which helps to process this huge amount of data".
Chen et al. (2012)	Big data and big data analytics are used to "describe the data sets and analytical techniques in applications that are so large (from terabytes to exabytes) and complex (from sensor to social media data) that they require advanced and unique data storage, management, analysis, and visualization technologies."
Davenport (2014)	Big data is "a new resolve to apply powerful data-gathering and analysis methods not just to a company's operations but also to its offerings to embed data smartness into the products and services customers buy."
Gunasekaran et al. (2017)	Big data is to "help address critical challenges of predictive analytics that refer to data capture, storage, transfer & sharing (i.e. system architecture), and search, analysis, and visualization (i.e. data analytics)."
Lee et al. (2014)	Big data is "a powerful strategic resource for uncovering unforeseen patterns and developing sharper insights about customers, businesses, markets and environments".
Liu (2013)	Big data refers to "large, diverse, complex, longitudinal, or distributed data sets generated from instruments, sensors, Internet transactions, email, video, click streams, and all other digital sources available today and in the future".
McAfee and Brynjolfsson (2012)	Big data is used to "glean intelligence from data and translate that into business advantage".
Manyika et al. (2011)	Big data refers to "datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze."
Wang, Kung, and Byrd (2018)	From the information lifecycle management (ILM) view, big data capability can be defined as "the ability to acquire, store, process and analyze large amount health data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion."

Source: Adapted from Sun, Hall, and Cegielski (2020)

A review of these definitions reveals two main perspectives. First, BD is viewed as a technological innovation enabling large-scale data processing and analytics (Chen et al., 2015; Liu, 2013). Second, BD is framed as a strategic enabler that enhances

decision-making, competitiveness, and customer understanding (Davenport, 2014; Lee et al., 2014). These complementary views highlight that BD's value lies not only in the data itself but also in the organisational capability to transform it into actionable insights.

In the context of SMEs, BD functions as a critical managerial tool to improve decision quality, enhance efficiency, reduce operational costs, and strengthen market responsiveness. By adopting BD solutions, SMEs can compete more effectively in dynamic markets and align their strategies with digital transformation trends in both developed and developing economies.

2.3 Differences Between Big Data And Traditional Data

BD differs from traditional data in several dimensions, including data source, volume, variety, velocity, storage, integration, and access. Table 2.2 summarises the main distinctions between BD and traditional data systems.

Universiti Utara Malaysia

Table 2.2
Differences Between Big Data and Traditional Data

Category	Big data	Traditional small data
Type of data source	It includes data generated from real-time analysis (distributed data) • Genomic data • Social media data • Web log data • Streaming data	Traditional enterprise data (centralized data) • Customer relationship management systems • Financial data • Student data
Volume of data generated	•Terabytes • Petabytes • Exabytes • Zettabytes	• Gigabytes • Terabytes
Data variety	It may be structured, semi-structured or unstructured	It may be structured or semi structured. Does not support unstructured data
Data velocity	Often real-time data generated on hourly or daily basis. It requires immediate response	Data generated in batch mode or near real time, more rapidly than big data. It does not require immediate response
Data storage	NoSQL, HDFS	RDBMS
Data integration	Difficult	Easy

Data access	Interactive	Batch or near real time

Source: Adapted from Nagaraj et al. (2018).

In summary, BD operates within an ecosystem of large-scale, diverse, and fast-moving data, whereas traditional data remains confined to structured and smaller datasets managed through centralised systems. The fundamental distinction lies in BD's ability to generate real-time insights, which enables organisations, including SMEs, to make more responsive and data-driven decisions compared with conventional analytical systems.

2.4 Big Data Applications

Effective utilisation of BD requires the selection of suitable analytical tools and platforms, such as Hive, MongoDB, Cloudera, and Hadoop, which support data collection, processing, and analysis. Although these tools provide advanced analytical capabilities, they also demand a high level of technical competence (Rajabion, 2018).

In recent years, SMEs have increasingly joined larger corporations in leveraging BD to enhance performance, improve operational efficiency, and understand customer behaviour. The evolution of BD tools and analytical technologies continues to influence SMEs' ability to integrate BD into decision-making and strategic planning. However, limited technical expertise and resource constraints remain major barriers to adoption (Gangwar, 2018).

Simpler and more user-friendly technologies generally show higher adoption rates (Alshamaila et al., 2013; Chaudhury & Bharati, 2008; Igbaria et al., 1995). Yet, managing BD through complex domains such as Apache Hadoop, Spark, NoSQL databases, deep learning, machine learning, and data visualisation poses challenges for firms lacking skilled personnel. These processes involve data acquisition, storage,

transformation, and analysis, which require both technical capacity and organisational readiness.

2.5 Big Data for SMEs: Benefits and Challenges

BD has become a key driver of innovation, efficiency, and competitiveness across all business sectors. For small and medium enterprises (SMEs), BD presents significant opportunities to enhance strategic and operational performance. BD enables data-driven decision-making, improving forecasting accuracy and responsiveness to market trends (Davenport, 2014; Lee et al., 2014). It enhances cost efficiency by automating data collection and analysis, thereby reducing manual work and improving resource utilization (Gunasekaran et al., 2017). BD also strengthens customer insight and market intelligence, allowing SMEs to identify behavioural patterns and tailor products or services accordingly (McAfee & Brynjolfsson, 2012). Moreover, it supports innovation and competitiveness by enabling firms to explore new opportunities, anticipate risks, and improve overall decision quality (Chen et al., 2012; Manyika et al., 2011).

However, despite these clear advantages, BDA among SMEs remains limited and slow, especially in developing economies. This gap can be explained through three key dimensions of the TOE framework technological, organisational, and environmental factors.

From a technological perspective, SMEs often lack the infrastructure and analytical tools required for BD processing. Complex systems such as Hadoop, Spark, or NoSQL databases demand technical expertise that many SMEs cannot afford. Data quality,

integration, and security issues further discourage firms from adopting BD solutions (Gangwar, 2018; Maroufkhani et al., 2023).

From an organisational perspective, limited managerial awareness, weak strategic vision, and resistance to change hinder adoption. Many SME leaders perceive BD as complex, costly, and uncertain in terms of return on investment (Alshamaila et al., 2013). Financial and human-resource limitations restrict their ability to hire data specialists or invest in training, thereby reducing organisational readiness and innovation capacity.

From an environmental perspective, inadequate governmental support, insufficient external vendor assistance, and weak competitive pressure contribute to slow adoption. SMEs in developing countries often operate in unstable markets with minimal policy incentives or digital infrastructure. The absence of reliable vendor networks and limited governmental funding further exacerbates these constraints, making BDA riskier and less accessible.

Universiti Utara Malaysia

Nevertheless, SMEs' flexibility and entrepreneurial orientation can serve as enablers once fundamental barriers are addressed. Their flatter hierarchies allow faster decision-making and adaptability to technological change when supported by sufficient resources and knowledge (Park & Kim, 2021; Verma & Chaurasia, 2019).

In summary, BD offers SMEs immense potential to improve competitiveness, innovation, and performance. Yet, technological limitations, organisational weaknesses, and environmental constraints collectively explain the slow diffusion of BD, particularly in developing and conflict-affected economies. Understanding these

benefits and challenges provides the rationale for investigating the Intention to Adopt IABD within the TOE framework and justifies the need for this study.

2.6 Definition and Role of SMEs

Globally, SMEs are recognised as essential drivers of employment, innovation, and economic growth. Their classification, however, varies across countries, depending on criteria such as the number of employees, annual turnover, and registered capital. For instance, the European Union defines SMEs as enterprises employing fewer than 250 people, while the World Bank classifies them based on a turnover threshold of up to USD 15 million (OECD, 2021). Although definitions differ, the common principle is that SMEs represent firms operating at a smaller scale than large corporations but with substantial contributions to productivity, innovation, and local development.

In the Palestinian context, SMEs play a vital role in economic resilience and social stability, particularly under conditions of political and financial constraint. According to the Palestinian Central Bureau of Statistics (PCBS, 2022), SMEs constitute approximately 98% of all registered enterprises in the country and are a major source of employment. They operate across diverse sectors including trade, manufacturing, services, agriculture, and technology-driven industries (Alfoqahaa, 2018).

The Palestinian Council of Ministers (2011) established specific quantitative criteria to categorise enterprises, as shown in Table 2.3. These thresholds are used for policy, taxation, and development purposes and provide a framework for distinguishing micro, small, and medium enterprises.

Universiti Utara Malaysia

Table 2.3
Classification of Palestinian Enterprises

Type of enterprises	Number of employees	Annual revenue in USD	Registered capital in USD
Micro	1-4	20,000	5000
Small	5-9	20,001-200,000	50,001-50,000
Medium	10-19	200,001-500,00	50,001-100,000
Large	20-over	500,001-over	100,001-over

Source: Palestinian Council of Ministers (2011)

SMEs in Palestine thus serve as the backbone of the national economy, contributing to income generation, entrepreneurship, and employment. Their structural simplicity and flexibility enable them to adapt quickly to market shifts, yet they often face significant obstacles, including restricted access to finance, limited technological infrastructure, and weak institutional support. These conditions make them a compelling context for examining the IABD, particularly within developing economies where resource constraints are prevalent.

2.7 Intention to Adopt Big Data

The IABD reflects the extent to which a firm is willing and prepared to implement BD in its operations. It represents a crucial pre-adoption stage, where decision-makers evaluate the potential benefits, feasibility, and risks of adoption before committing resources (Asiaei & Ab. Rahim, 2019). In this stage, firms assess how BD aligns with their strategic goals, technological capabilities, and organisational readiness.

IABD serves as a predictor of actual adoption behaviour and is influenced by both internal and external factors. From the perspective of the TOE framework, technological factors (such as perceived RADV, COMP, and CMPLX) influence the perceived usefulness and ease of BD integration. Organisational factors (including TMS, OR, and INNOV) determine the firm's ability and motivation to adopt, while environmental conditions (such as COMPR, EXSUPP, and GOVS) create external

pressures or support that shape adoption decisions (Tien et al., 2020).

Empirical studies have shown that SMEs often demonstrate positive intentions toward adopting BD but face challenges translating these intentions into actual implementation due to financial, technical, and knowledge limitations (Ka & Kim, 2014; Wahab & Olugu, 2018). Research in developing economies, including Malaysia, has highlighted several determinants of IABD, such as IT infrastructure, data security, financial capacity, skills and experience, and market competition (Tien et al., 2020). These factors collectively influence whether an SME perceives BD adoption as feasible and beneficial for achieving competitive advantage.

In the context of this study, IABD is considered a key behavioural construct that links the perceived benefits and challenges of BD to actual adoption outcomes. Understanding the factors influencing the IABD provides valuable insight into how SMEs form adoption decisions and respond to technological, organisational, and environmental influences.

Universiti Utara Malaysia

2.8 Technology–Organization– Environment (TOE)

The TOE framework, introduced by Tornatzky and Fleischer (1990), identifies the technological, organisational, and environmental contexts that influence technology adoption within firms. It provides a comprehensive structure for analysing how internal and external conditions shape the decision to adopt new technologies. The framework has been widely applied in studies examining innovation adoption across different settings, including cloud computing, e-commerce, enterprise systems, and social media (Amoah et al., 2023; Boonsiritomachai et al., 2016; Hassan, 2017; Shahadat et al., 2023; Tamin & Adis, 2022).

However, despite its extensive use, previous research applying TOE to SMEs has often treated the framework in a generic manner, without accounting for the unique characteristics of smaller firms such as resource scarcity, informal structures, and limited digital capabilities (Lai et al., 2018; Grant & Yeo, 2018). These studies frequently assumed that factors influencing large organisations apply equally to SMEs, which limits the generalisability of their findings. To address this limitation, the present study adapts the TOE framework by integrating INNOV as a moderating variable, thereby capturing how innovation-oriented behaviour strengthens or weakens the effects of TOE dimensions on IABD.

The choice of TOE for this study is based on several considerations. First, it provides a multi-dimensional view of technology adoption by combining internal (technological and organisational) and external (environmental) determinants (Yadegaridehkordi et al., 2020). Second, it includes the environmental dimension, which is absent in models such as DOI and Technology Acceptance Model (TAM) but crucial for SMEs operating in dynamic and uncertain markets (Ghazi Naji et al., 2022). Third, the TOE framework's adaptability allows researchers to extend or customise its constructs to suit specific research contexts, such as BDA in developing economies.

Accordingly, this study employs the TOE framework as its theoretical foundation to examine the factors influencing the IABD among SMEs. The model's comprehensiveness and flexibility make it particularly appropriate for understanding the combined effects of technological, organisational, and environmental factors within the resource-constrained environment in which SMEs operate.

Universiti Utara Malaysia

2.8.1 Technological Factors

The technological context of the TOE framework refers to the internal and technical characteristics that influence an organisation's readiness and capability to adopt new technologies (Tornatzky & Fleischer, 1990). In the context of BDA, these factors are consistent with the DOI model developed by Rogers (2003), which identifies five key attributes RADV, COMP, CMPLX, TR, and OB as essential factors influencing the innovation adoption (Saetang et al., 2020; Verma & Chaurasia, 2019).

Within SMEs, technological factors shape managers' perceptions of BD's usefulness, practicality, and ease of integration. RADV reflects the perceived improvement BD offers over existing technologies, such as higher performance, data-driven decision-making, and operational efficiency. COMP measures how well BD fits with existing systems and workflows, while CMPLX indicates the perceived difficulty of implementation and use. TR allows experimentation before full-scale adoption, and OB represents the visibility of BD's outcomes, which enhances confidence and reduces uncertainty.

Empirical evidence shows that RADV, COMP, and CMPLX are among the most influential determinants of technology adoption in SMEs (Agrawal, 2015; Sun et al., 2020; Tsai et al., 2010). However, TR and OB also play important roles by enabling experimentation and peer learning, especially in resource-constrained environments (Alshamaila et al., 2013; Ramdani et al., 2013). Collectively, these technological factors provide a comprehensive understanding of how the perceived attributes of BD influence SMEs' IABD.

Universiti Utara Malaysia

2.8.1.1 Relative advantage and Intention or Adoption of Big Data.

Within the DOI and TOE frameworks, RADV refers to the degree to which an innovation is perceived to provide greater benefits than existing alternatives (Rogers, 2003). It represents a key driver of technology adoption because organisations are more likely to adopt an innovation when they perceive clear economic or operational advantages (Alshamaila et al., 2013; Ramdani et al., 2013). In the context of BD, RADV captures the perceived potential to enhance decision-making, reduce costs, and improve competitiveness through the integration of data analytics into strategic and operational processes.

Empirical research consistently supports the influence of RADV on both adoption and IABD. Studies in China, Korea, and Sri Lanka have shown that firms perceiving BD as beneficial to efficiency and performance exhibit stronger IABD (Lai et al., 2018; Jang et al., 2019; Mahesh et al., 2018). Similar findings were reported across Malaysia, India, Iran, and Jordan, where RADV was a significant determinant of BDA in SMEs operating in manufacturing, hospitality, and service sectors (BDA enhances business operations by enabling data-driven decision-making, boosting efficiency, competitiveness, and innovation. While large enterprises have successfully adopted BDA, SMEs face significant adoption challenges, creating a notable gap compared to larger enterprises (Lutfi et al., 2022a; Verma & Chaurasia, 2019; Nasrollahi et al., 2021). Despite growing awareness of BDA's benefits, adoption rates among SMEs remain critically low, limiting their ability to leverage data for growth and sustainability.

A more recent study by Abulehia et al. (2023) confirmed this relationship among

Universiti Utara Malaysia

Palestinian SMEs, reinforcing the central role of perceived advantage in shaping BDA behaviour.

Nevertheless, a few studies have reported non-significant relationships between RADV and BDA (Maroufkhani et al., 2020b; Nam et al., 2015), suggesting that perceived benefits alone may not guarantee adoption, particularly where financial, technical, or institutional barriers exist. This inconsistency highlights the need to examine how RADV influences IABD in resource-constrained environments.

In developing economies and especially within SMEs in conflict-affected regions such as Palestine limited resources and technological expertise require firms to adopt BD only when the expected benefits outweigh the costs and risks (Chuah & Thurusamry, 2021; Lutfi et al., 2022b). Therefore, exploring RADV in the context of IABD among SMEs in such environments offers valuable insight into how perceived advantages drive strategic technology decisions despite environmental challenges.

Universiti Utara Malaysia

2.8.1.2 Compatibility and Intention or Adoption of Big Data.

Within the TOE and DOI frameworks, COMP reflects the extent to which an innovation fits with an organisation's existing systems, culture, and operational processes (Rogers, 2003). When new technologies align closely with current practices and values, firms experience fewer disruptions and lower resistance to change, which enhances the likelihood of adoption (Chen et al., 2015; Ramdani et al., 2013). In the context of BD, high COMP allows SMEs to integrate data-driven tools with minimal modification to their infrastructure and workflows, thereby improving the efficiency and acceptance of adoption.

Empirical research has generally confirmed that COMP positively influences BDA and intention to adopt. Studies conducted in China, India, Malaysia, and Vietnam have found that when BD aligns with existing IT infrastructure and business strategies, SMEs are more likely to perceive it as feasible and valuable (Agrawal, 2016; Gangwar, 2018; Truong, 2022; Yadegaridehkordi et al., 2018). Similarly, Abulehia et al. (2023) and Mahesh et al. (2018) reported significant relationships between COMP and IABD, indicating that COMP encourages BDA in different organisational settings.

However, other studies have reported mixed or insignificant results, suggesting that COMP alone may not always determine adoption decisions (Lutfi et al., 2022b; Maroufkhani et al., 2020a; Park & Kim, 2021). These inconsistencies may be due to contextual factors such as firm size, technological readiness, and environmental uncertainty. In resource-constrained SMEs, even if BD is compatible with existing systems, adoption may still be limited by financial and technical challenges (Nasrollahi et al., 2021).

Universiti Utara Malaysia

Overall, COMP remains a vital determinant of IABD, as it reduces implementation costs and organisational disruption. Nonetheless, the divergent findings across countries and industries indicate that the strength of this relationship may depend on moderating variables such as INNOV. Few studies have examined how INNOV interacts with COMP to shape adoption behaviour, especially in developing and conflict-affected economies such as Palestine highlighting a significant research gap this study aims to address.

2.8.1.3 Complexity and Intention or Adoption of Big Data.

Within the TOE and DOI frameworks, CMPLX refers to the extent to which a technology is perceived as difficult to understand, implement, or use (Rogers, 2003). High levels of perceived CMPLX often discourage adoption because they increase uncertainty, implementation costs, and the need for technical expertise (Verma & Chaurasia, 2019; Jang et al., 2019). In the context of BD, CMPLX may stem from the lack of standardised tools, integration challenges with existing systems, or the financial and human resource requirements for managing advanced analytics (Agrawal, 2015).

Empirical research has generally found that CMPLX negatively influences both BDA and IABD. Studies in India, Malaysia, and Jordan reported that SMEs perceiving BD as complex were less likely to adopt or intend to adopt it (Baig et al., 2023; Lutfi et al., 2022b; Verma & Bhattacharyya, 2017). Similar results have been observed in Iran and Sri Lanka, where technological sophistication and integration costs limited BD implementation among resource-constrained firms (Mahesh et al., 2018; Nasrollahi et al., 2021). However, some studies have shown no significant effect of CMPLX on adoption (Lai et al., 2018; Park & Kim, 2021), suggesting that its impact may vary depending on contextual factors such as managerial expertise, firm size, and technological readiness.

Universiti Utara Malaysia

These mixed findings indicate that while CMPLX is generally an inhibitor, its influence can be moderated by organisational capabilities and innovation culture. In SMEs, managers' confidence in handling BD tools and their perception of ease of use can reduce the perceived CMPLX, making adoption more feasible. Nevertheless, few studies have explored how INNOV may moderate the relationship between CMPLX

and IABD, particularly in developing or conflict-affected contexts like Palestine. Addressing this gap provides an opportunity to understand how organisational characteristics can offset the negative effects of perceived CMPLX on BDA decisions.

2.8.1.4 Trialability and Intention or Adoption of Big Data.

Within the DOI and TOE frameworks, TR refers to the extent to which a firm can experiment with a new technology before full-scale adoption (Rogers, 2003). For SMEs, TR plays a critical role because it allows decision-makers to test BD tools on a limited scale, gain hands-on experience, and evaluate potential benefits while minimising uncertainty and risk (Alshamaila et al., 2013). Through pilot implementation or trial versions, firms can better understand the operational requirements of BD and identify integration challenges before committing major resources.

Empirical findings on TR have been mixed. Some studies have identified TR as a significant enabler of BDA and intention to adopt (Sharma et al., 2023; Maroufkhani et al., 2020b), while others found its influence to be relatively weaker compared to other technological factors (Sun et al., 2018; Yadegaridehkordi et al., 2018). These variations may reflect differences in the availability of trial opportunities, the cost of BD solutions, and the readiness of SMEs to engage in experimental adoption.

Despite its varying significance, TR remains an important factor in explaining IABD, particularly in contexts where SMEs face financial and technical constraints. The ability to test BD systems before full deployment helps managers reduce perceptions of CMPLX, improve confidence in outcomes, and facilitate organisational learning. However, few studies have explored the role of TR in developing or conflict-affected

economies, where limited vendor support and infrastructure may restrict access to trial-based adoption strategies. Investigating TR within such contexts, therefore, contributes to a more nuanced understanding of how SMEs build confidence in adopting BD innovations.

2.8.1.5 Observability and Intention or Adoption of Big Data.

Within the DOI and TOE frameworks, OB refers to the extent to which the outcomes of an innovation are visible to others (Rogers, 2003). In the context of BD, OB enables SMEs to observe how other firms successfully implement and benefit from BD solutions, which reduces uncertainty and strengthens confidence in the decision to adopt. When the tangible advantages of BD such as improved efficiency, customer insight, and competitiveness are observable in similar organisations, SMEs are more likely to perceive adoption as a safe and valuable investment.

Empirical evidence supports the positive influence of OB on BDA and IABD, particularly in industries where visibility and peer comparison are strong motivators (Mahesh et al., 2018; Sam & Chatwin, 2019). SMEs tend to emulate competitors that demonstrate measurable benefits from BD utilization, perceiving adoption as essential to remain competitive. In contrast, some studies have found the effect of OB to be insignificant, suggesting that in contexts with limited market transparency or weak communication networks, SMEs may lack sufficient exposure to successful BD examples (Yadegaridehkordi et al., 2018; Maroufkhani et al., 2020b).

Overall, OB acts as a social and informational mechanism that facilitates learning and reduces perceived risk in the adoption process. By witnessing the success of early adopters, SMEs can evaluate BD's practical value before investing significant

resources. However, in developing or conflict-affected economies such as Palestine, low inter-firm collaboration and restricted access to innovation networks may weaken the effect of OB on IABD. Understanding how visibility and shared experiences influence adoption behavior thus remains a key aspect of this study's investigation.

2.8.2 Organisational Factors

The organisational factors represents the second dimension of the TOE framework and encompasses internal characteristics that shape an organisation's ability to adopt and implement technological innovations (Tornatzky & Fleischer, 1990). These factors include both tangible resources such as financial capacity, infrastructure, and skilled personnel and intangible elements such as leadership commitment, communication, and organisational culture (Gangwar, 2018). In the context of BD, the organisational factors determines how effectively a firm can integrate data-driven tools into its operations and align them with strategic objectives (Chatterjee et al., 2022; Iranmanesh et al., 2023).

Universiti Utara Malaysia

Empirical studies have shown that strong organisational conditions accelerate BDA within SMEs, while weak internal structures, limited managerial support, and lack of readiness often hinder progress (El-Haddadeh et al., 2021; Lutfi et al., 2022b; Shahadat et al., 2023). Two factors are consistently highlighted as central to this process: TMS, which reflects leadership commitment to innovation and resource allocation, and OR, which encompasses the technical, financial, and human capacities necessary to adopt BD (Lai et al., 2018; Rajabion, 2018; Yadegaridehkordi et al., 2018).

For this study, these organisational dimensions are critical in explaining variations in IABD among SMEs. Both TMS and OR are expected to influence managers'

willingness and preparedness to adopt BD technologies, particularly within resource-constrained environments such as Palestine. Understanding how these internal organisational enablers interact with technological and environmental contexts provides essential insights into the factors shaping BDA intentions.

2.8.2.1 Top Management Support and Intention or Adoption of Big Data.

Within the TOE framework, TMS represents the extent to which senior executives demonstrate commitment, allocate resources, and provide leadership to support technological innovation (Ramdani & Kawalek, 2007). In the context of SMEs, TMS is essential because it determines the level of strategic focus and resource mobilisation required to implement complex technologies such as BD (Maroufkhani et al., 2020a). Managers who actively champion innovation are better positioned to overcome organisational resistance, foster a supportive culture, and ensure that adoption aligns with business goals (Shahbaz et al., 2021).

Universiti Utara Malaysia

Empirical studies consistently indicate that TMS positively influences both the adoption and the IABD across various sectors and countries. Research in China, Malaysia, and Jordan found that strong managerial commitment and resource allocation enhanced the likelihood of BDA (Jang et al., 2019; Sun et al., 2020; Lutfi et al., 2022b). Similarly, Sharma et al. (2023) and Yadegaridehkordi et al. (2018) ranked TMS among the top organisational enablers influencing BDA. These studies suggest that leadership vision and direct involvement from senior managers are crucial in addressing uncertainties associated with BD technologies.

However, other studies have found TMS to be insignificant in influencing technology adoption, particularly in smaller or less formalised organisations (Lindawati et al.,

2023; Oliveira et al., 2014). In such contexts, decision-making may be decentralised, or managers may lack the expertise and motivation to support technological innovation (Ramdani & Kawalek, 2008). These inconsistencies imply that the impact of TMS may depend on contextual variables such as firm size, culture, and resource availability.

In developing and conflict-affected contexts such as Palestine, the role of TMS becomes even more critical. Limited financial resources, poor infrastructure, and restricted access to modern communication technologies hinder the implementation of BD. Under such constraints, proactive managerial leadership is necessary to secure resources, build partnerships, and motivate employees to engage in innovative practices despite environmental challenges.

In conclusion, while TMS is widely recognised as a key driver of technological adoption, its effectiveness may vary across organisational and environmental contexts. The moderating role of INNOV is therefore essential to understanding how leadership commitment interacts with innovation culture to shape IABD among SMEs operating under resource limitations such as those in Palestine.

Universiti Utara Malaysia

2.8.2.2 Organisational Readiness and Intention or Adoption of Big Data.

Within the TOE framework, OR refers to the extent to which a firm possesses the technological, financial, and human resources required to adopt and implement innovation effectively (Chen et al., 2015; Gangwar, 2018; Maroufkhani et al., 2020a). It reflects both the organisation's capability and willingness to allocate resources and adapt processes to support technological change. Firms with strong OR are more likely to perceive new technologies such as BD as feasible and beneficial, while those with limited readiness may view adoption as risky or unattainable (El-Haddadeh et al.,

2021).

Empirical evidence generally supports the significant role of OR in influencing both adoption and IABD. Studies conducted in Malaysia, Jordan, and Iran reported that OR positively affects the adoption of BD in SMEs by ensuring that sufficient infrastructure, skills, and investment are available (Baig et al., 2023; Lutfi et al., 2022b; Yadegaridehkordi et al., 2020). Similarly, Abulehia et al. (2023) found that OR significantly predicts IABD among Palestinian SMEs, highlighting the importance of internal capacity in overcoming technological and financial barriers.

However, some studies have found no significant relationship between OR and BDA (Angwar, 2018; Maroufkhani et al., 2023). These discrepancies may arise when firms have already achieved a baseline level of technological maturity, making additional readiness factors less influential. In other cases, organisations may compensate for limited readiness by relying on external partnerships or vendor support.

Universiti Utara Malaysia

In developing and conflict-affected environments such as Palestine, SMEs face structural obstacles including limited access to ICT infrastructure, financial constraints, and shortages of skilled IT professionals. The ongoing blockade and restrictions on advanced communication technologies exacerbate these challenges, making OR a critical determinant of successful BD implementation. Under such conditions, proactive leadership and effective resource management become essential for enabling adoption.

In conclusion, while OR is widely recognized as a determinant of technology adoption, its influence on IABD remains inconsistent across contexts. Investigating the moderating role of INNOV in the relationship between OR and IABD provides an

opportunity to understand how innovation culture strengthens the capacity of SMEs to adopt BD, particularly within the challenging context of Palestine.

2.8.3 Environmental Factors

The environmental factors represents the third dimension of the TOE framework and refers to external elements that shape an organisation's technological decisions (Tornatzky & Fleischer, 1990). It includes the broader business environment in which firms operate such as market competition, regulatory frameworks, and relationships with technology providers that can either facilitate or hinder adoption. For SMEs, the environmental factors are particularly influential because these firms often depend on external support and market dynamics to compensate for limited internal resources (Ghaleb et al., 2021; Verma & Chaurasia, 2019).

Within the context of BDA, three environmental factors are frequently identified as key determinants: COMPR, EXSUPP, and GOVS. COMPR refers to the external pressure from competitors that motivates firms to adopt new technologies to remain competitive. EXSUPP captures the technical and advisory assistance provided by technology vendors, consultants, or service providers, which reduces the uncertainty and cost associated with BDA. GOVS represents the extent of public-sector initiatives, incentives, and policies that encourage or facilitate technological innovation.

Empirical research suggests that these factors collectively shape firms' IABD, particularly in SMEs, where external support often compensates for a lack of internal capacity (Lutfi et al., 2022b; Nasrollahi et al., 2021). For example, competitive market environments increase pressure on firms to innovate, while access to reliable vendors and supportive government policies can significantly lower perceived risks and

financial barriers.

In the case of Palestine, these environmental influences are shaped by exceptional political and infrastructural constraints. Restricted access to modern ICT infrastructure, limited governmental digital initiatives, and weak vendor networks reduce the availability of external support mechanisms that could facilitate BDA. As such, understanding how COMPR, EXSUPP, and GOVS interact with technological and organisational conditions is crucial for explaining IABD among Palestinian SMEs operating under these challenging circumstances.

2.8.3.1 Competitive Pressure and Intention or Adoption of Big Data.

Within the TOE framework, COMPR represents the extent to which external market forces such as competitors, suppliers, and customers motivate firms to adopt new technologies to maintain or improve their competitive position (Oliveira et al., 2014). In dynamic and technology-driven environments, firms facing intense competition are more likely to perceive innovation as a strategic necessity rather than an option (Tsai et al., 2010).

Empirical studies have generally confirmed a positive association between COMPR and both BDA and IABD. Research in China, Korea, Sri Lanka, and Malaysia found that heightened market rivalry encourages firms to adopt BD to enhance operational efficiency, customer insight, and strategic agility (Abulehia et al., 2023; Jang et al., 2019; Mahesh et al., 2018; Sun et al., 2020; Yadegaridehkordi et al., 2020). Similarly, studies from India and Thailand demonstrated that competitive intensity compels firms to leverage BD to differentiate their offerings and sustain performance advantages (Gangwar, 2018; Verma & Chaurasia, 2019).

However, several studies reported non-significant relationships between COMPR and BDA (Lutfi et al., 2022b; Maroufkhani et al., 2020a; Park & Kim, 2021). These inconsistencies are often attributed to limited global exposure, weak local competition, and constrained market openness factors that reduce pressure on firms to innovate. In developing contexts, where industries are less digitised, the influence of COMPR tends to diminish because firms prioritise survival and resource efficiency over technological competition.

In the Palestinian context, SMEs face restricted international integration and limited access to advanced technologies due to the blockade and political instability. Consequently, competitive dynamics are often localised and less influenced by global technological trends. Understanding how COMPR interacts with organisational characteristics such as INNOV is therefore critical to explaining IABD. Examining this relationship provides insight into how perceived competition drives or fails to drive technology adoption in resource-constrained and conflict-affected environments.

Universiti Utara Malaysia

2.8.3.2 External Vendors Support and Intention or Adoption of Big Data.

Within the TOE framework, EXSUPP refers to the extent to which technology providers, consultants, or third parties offer technical, financial, and advisory assistance to facilitate adoption (Al-Qirim, 2007). For SMEs, EXSUPP is critical because it compensates for limited internal IT expertise and resource constraints by providing access to external knowledge and problem-solving capabilities (Maroufkhani et al., 2020b). Effective vendor relationships not only involve the provision of hardware or software but also include ongoing consultation, troubleshooting, and customised training to ensure successful technology

implementation (Nguyen et al., 2022).

Empirical studies consistently demonstrate that EXSUPP has a significant positive influence on BDA and IABD. Research across Malaysia, Vietnam, India, and Iran confirmed that EXSUPP enhances adoption readiness by reducing implementation complexity and cost barriers (Gangwar, 2018; Nasrollahi et al., 2021; Nguyen et al., 2022; Yadegaridehkordi et al., 2020). Vendors play a facilitative role by offering scalable tools, flexible pricing, and post-adoption assistance that enable SMEs to sustain innovation processes.

However, in developing and conflict-affected economies, the effect of EXSUPP may be limited by weak vendor networks, lack of localisation, and financial barriers. In the Palestinian context, restricted access to advanced technologies, the scarcity of skilled personnel, and infrastructure instability make vendor collaboration essential. Vendors can help bridge these gaps by offering affordable solutions, online training, and continuous technical support tailored to SMEs' capabilities.

Universiti Utara Malaysia

Despite the recognised importance of EXSUPP, few studies have examined its effect on IABD in fragile economies. Investigating how INNOV moderates the relationship between EXSUPP and IABD will provide valuable insights into how external partnerships and organisational innovation jointly facilitate BDA under resource constraints.

2.8.3.3 Governmental Support and Intention or Adoption of Big Data.

Within the TOE framework, GOVS refers to the degree of governmental facilitation, incentives, and regulatory support that encourages firms to adopt innovative

technologies (Park & Kim, 2021; Nguyen et al., 2022). Governmental interventions such as financial assistance, tax incentives, public data access, and training initiatives reduce the risks associated with adopting complex technologies like BD (Maroufkhani et al., 2020a). Effective policies and institutional frameworks can therefore accelerate adoption by improving awareness, technical readiness, and confidence among SMEs.

Empirical studies consistently demonstrate that GOVS positively influences both BDA and IABD. Research in China, Korea, Malaysia, and Vietnam has shown that when governments provide infrastructure investment, training programs, and digital innovation policies, SMEs are more likely to integrate BD into their operations (Baig et al., 2023; Ghaleb et al., 2021; Jang et al., 2019; Nguyen et al., 2022; Yadegaridehkordi et al., 2018). Similarly, studies in Jordan and Sri Lanka confirmed that government-led initiatives play a central role in reducing adoption barriers (Lutfi et al., 2022b; Mahesh et al., 2018).

Universiti Utara Malaysia

However, contrasting findings exist. Some studies reported no significant impact of GOVS on adoption, particularly in contexts where policy implementation is weak or incentives are insufficient (Maroufkhani et al., 2020b). This inconsistency may arise when firms perceive government interventions as unreliable, overly bureaucratic, or detached from industry needs.

In Palestine, the situation is further complicated by political division, economic instability, and infrastructure challenges. The existence of two administrative authorities, coupled with a long-standing blockade and restrictions on technological imports, has constrained the government's ability to provide consistent policy support or incentives for SMEs. Consequently, limited governmental capacity weakens

national digitalisation efforts and undermines firms' motivation to adopt BD technologies.

Given these conditions, examining GOVS within the Palestinian context offers valuable insight into how policy limitations affect technological diffusion. Moreover, exploring the moderating role of INNOV in the relationship between GOVS and IABD can reveal how internally driven innovation may compensate for weak institutional support in resource-constrained and conflict-affected environments.

2.9 Organisational Innovativeness

INNOV refers to an organisation's willingness and ability to embrace new ideas, methods, and technologies to improve processes, products, and decision-making (Kirton, 2003; Marcati et al., 2008). Within SMEs, INNOV reflects not only structural adaptability but also the mindset and leadership orientation particularly the CEO's openness to experimentation and risk-taking (Agarwal & Prasad, 1998; Thong, 1999). Firms characterized by higher INNOV levels tend to adopt new technologies such as BD earlier, integrate them more effectively, and derive stronger competitive advantages (Alshamaila et al., 2013; Asiaei & Ab. Rahim, 2019; Shahadat et al., 2023).

From a theoretical standpoint, INNOV can be conceptualized as both an organisational capability and a behavioural disposition. As a capability, it shapes how firms reconfigure internal resources and learning systems to accommodate technological change (Gallego et al., 2013). As a behavioural attribute, it captures leadership-driven readiness to challenge routines, absorb uncertainty, and transform knowledge into new practices (Premkumar & Roberts, 1999; Yeşil et al., 2013). This dual perspective makes INNOV a critical element within the TOE framework, bridging internal and

Universiti Utara Malaysia

external contexts by influencing how technological opportunities are recognized and acted upon.

Empirical evidence across diverse contexts reinforces INNOV's importance in technology adoption. Studies have demonstrated its positive impact on the adoption of ICT (Shahadat et al., 2023), blockchain (Malik et al., 2021), cloud computing (Asiaei & Ab. Rahim, 2019), e-business transformation (Lin et al., 2020), and semantic web technologies (Kim et al., 2018). These findings converge on the view that innovative organisations are more responsive to technological turbulence and more capable of converting external pressures into strategic actions. However, the majority of these studies treat INNOV as a direct determinant rather than a moderating mechanism, leaving its integrative role within complex adoption frameworks underexplored.

A critical review of TOE-based BD studies reveals inconsistent results across the ten antecedent factors technological (RADV, COMP, CMPLX, TR, OB), organisational (TMS, OR), and environmental (COMPR, EXSUPP, GOVS). While some studies consistently find significant effects (e.g., RADV and TMS), others report weak or conflicting relationships (e.g., COMP, OR, GOVS) (Agrawal, 2015; Jang et al., 2019; Maroufkhani et al., 2023; Park & Kim, 2021; Verma & Chaurasia, 2019). These discrepancies suggest that the influence of each TOE factor on IABD may depend on contextual conditions and internal firm characteristics an observation consistent with Baron and Kenny's (1986) principle that moderation can explain variance in weak or unstable relationships.

In this regard, INNOV serves as a theoretically and empirically grounded moderator that may amplify or buffer the effects of TOE factors on IABD. For instance, highly

Universiti Utara Malaysia

innovative firms may perceive RADV more strongly, interpret COMPR as an opportunity rather than a threat, and mobilize resources to overcome CMPLX or limited EXSUPP. Conversely, firms with low INNOV may remain risk-averse, perceiving technological and environmental uncertainties as barriers rather than catalysts. Thus, INNOV does not merely coexist with TOE constructs it dynamically interacts with them, shaping how SMEs interpret, prioritize, and act upon adoption stimuli.

The moderating perspective of INNOV has gained limited empirical attention in BDA research. Some recent works have proposed similar conceptual roles for variables such as organisational learning capability (Brock & Khan, 2017), environmental turbulence (Lai et al., 2018), or industry characteristics (Pu et al., 2018), but none have systematically integrated INNOV across all TOE dimensions. Park and Kim (2021) specifically emphasized the need to test INNOV's moderating influence within the TOE context, arguing that innovation-oriented organisations may experience distinct adoption trajectories compared to conservative ones.

In the Palestinian SME context, the moderating role of INNOV is especially relevant. Limited infrastructure, political instability, and resource scarcity constrain technological advancement, yet many SMEs exhibit entrepreneurial resilience and creativity. This contrast creates fertile ground for examining how internal innovativeness enables firms to navigate external adversity. SMEs with strong INNOV may be better positioned to interpret GOVS, EXSUPP, and COMPR as enabling conditions despite the broader economic constraints. Conversely, low-innovative firms may fail to exploit even favourable environmental opportunities.

Therefore, this study advances the field by positioning INNOV as a moderating construct within the integrated TOE framework to explain the IABD among SMEs. This contribution addresses a critical gap: no prior research has empirically examined how INNOV interacts simultaneously with all ten TOE factors (RADV, COMP, CMPLX, TR, OB, TMS, OR, COMPR, EXSUPP, GOVS) in shaping SMEs' intentions to adopt BD. By investigating this multidimensional moderation, the study enriches theoretical understanding, extends the TOE model's explanatory power, and provides a nuanced perspective applicable to SMEs in developing and conflict-affected economies.

2.10 Deployment Theories

Based on the study by Salisu et al. (2021), which employed a systematic literature review (SLR) and expert-ranking survey of 63 studies published in Scopus and WoS databases from 2011 to 2020, various theories, frameworks, and models have been used to explore the determinants of business intelligence systems (BIS) adoption. The most frequently used theories include the Technology-Organization-Environment (TOE) framework, Diffusion of Innovation (DOI) theory, and Institutional theory. Additionally, other models such as the IS adoption model for small businesses, Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behavior (TPB), Resource-Based View (RBV), and Technology Acceptance Model (TAM) have been utilized. These frameworks and models provide insights into BIS adoption at both the firm and individual levels, highlighting the complex nature of technology adoption in SMEs (Salisu et al., 2021).

This study employs the DOI theory and the TOE framework to comprehensively understand the factors influencing the adoption of BD among SMEs. The DOI theory

elucidates how innovations are communicated and adopted over time within social systems, focusing on key elements like RADV and OB. The TOE framework examines the technological, organisational, and environmental contexts affecting technology adoption. Additionally, this study explores the role of INNOV as a moderator, investigating how it influences the relationships between the DOI and TOE factors and the IABD. Integrating these theories and examining the moderating effect provides a robust framework for exploring the multifaceted interactions and determinants of big data adoption, offering valuable insights into the dynamics at play within Palestinian SMEs.

In the following section, the key theories used in technology adoption will be introduced.

2.10.1 The Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA), developed by social psychologists Martin Fishbein and Icek Ajzen in 1975, is a foundational theory in understanding human behavior. TRA posits that an individual's behavioral intentions are the most significant predictors of their actual behavior. These intentions are influenced by two main factors: attitudes towards behavior and subjective norms, as shown in Figure 2.1.

Attitudes towards the behavior refer to the individual's positive or negative evaluations of performing the behavior. This is determined by the individual's beliefs about the consequences of the behavior and their evaluations of these outcomes. If the outcomes are perceived positively, the attitude towards the behavior will be favorable, increasing the likelihood of the behavior being performed. Subjective norms, on the other hand, refer to the perceived social pressures to perform or not perform the behavior. These

norms consider the influence of important others, such as family, friends, and colleagues, and whether these individuals approve or disapprove of the behavior.

TRA has been widely applied in various fields, including health behavior, marketing, and information technology (IT) adoption. For instance, in health behavior studies, TRA has been used to predict behaviors such as smoking cessation, exercise, and healthy eating (Ajzen & Fishbein, 1980). In marketing, it has been applied to understand consumer purchase intentions and brand loyalty (Sheppard et al., 1988). In IT, TRA has helped explain users' acceptance of new technologies and systems (Davis, 1989).

Despite its widespread applicability, TRA was excluded from this study for several reasons. Firstly, TRA focuses primarily on individual-level factors and does not account for the complexity of organisational decision-making processes, which often involve multiple stakeholders and external influences. Secondly, TRA does not adequately address the rapid technological advancements and dynamic market conditions that characterize the adoption of BD technologies by SMEs. Lastly, empirical evidence suggests that while TRA is effective in predicting individual behaviors, its explanatory power diminishes in contexts involving complex, multifaceted decisions such as those found in organisational technology adoption (Venkatesh et al., 2003). Therefore, a more comprehensive theoretical framework, such as the Technology-Organization-Environment (TOE) framework, which includes technological, organisational, and environmental factors, was deemed more appropriate for this study.

Universiti Utara Malaysia

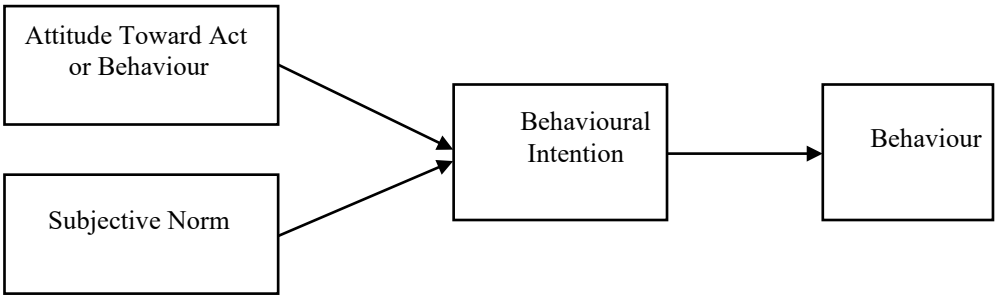


Figure 2.1
Theory of Reasoned Action
Source: Fishbein & Ajzen (1975)

2.10.2 The Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB), developed by Icek Ajzen in 1985, is a psychological theory that links beliefs and behavior. TPB is an extension of the TRA and is designed to predict and understand motivational influences on behavior that is not entirely under the individual's control. The core idea of TPB is that an individual's intention to engage in a behavior is the primary predictor of whether they will do so. This intention is influenced by three factors: attitude towards the behavior, subjective norms, and perceived behavioral control, as shown in Figure 2.2.

Attitude towards the behavior refers to the degree to which a person has a favorable or unfavorable evaluation of the behavior in question. It is determined by the individual's beliefs about the outcomes of the behavior and their evaluations of these outcomes. Subjective norms are the perceived social pressures to perform or not perform the behavior. This factor considers the influence of significant others, such as family, friends, and colleagues, and whether these individuals approve or disapprove of the behavior. Perceived behavioral control refers to the perceived ease or difficulty of performing the behavior and is assumed to reflect past experiences and anticipated obstacles. This component is similar to Bandura's concept of self-efficacy and is

Universiti Utara Malaysia

particularly important in understanding behaviors that individuals feel they have less control over.

TPB has been widely applied in various fields, including health psychology, environmental behavior, and IT adoption. For example, in the context of health behaviors, TPB has been used to predict behaviors such as smoking cessation, exercise, and dietary habits. In environmental studies, it has been applied to understand recycling behavior, water conservation, and energy-saving practices. In the realm of information systems (IS), TPB has helped explain users' acceptance of new technologies and systems (Ajzen, 1991; Armitage & Conner, 2001). Despite its broad applicability, TPB was excluded from this study for several reasons. Firstly, TPB focuses primarily on individual-level factors, while the current research aims to explore organisational-level determinants of behavior, particularly within the context of SMEs adopting BD technologies. The complexity of organisational decision-making processes often involves multiple stakeholders and external influences that TPB does not adequately address. Secondly, TPB does not sufficiently account for the rapid technological advancements and dynamic market conditions that characterize the technology adoption landscape today. Lastly, empirical studies suggest that while TPB is effective in predicting a wide range of behaviors, its explanatory power diminishes in contexts involving complex, multi-faceted decisions such as those found in organisational technology adoption (Venkatesh et al., 2012; Pavlou & Fygenson, 2006). Therefore, a more comprehensive theoretical framework that includes technological, organisational, and environmental factors, such as the TOE framework, is deemed more appropriate for this study, as shown in Figure 2.2.

Universiti Utara Malaysia

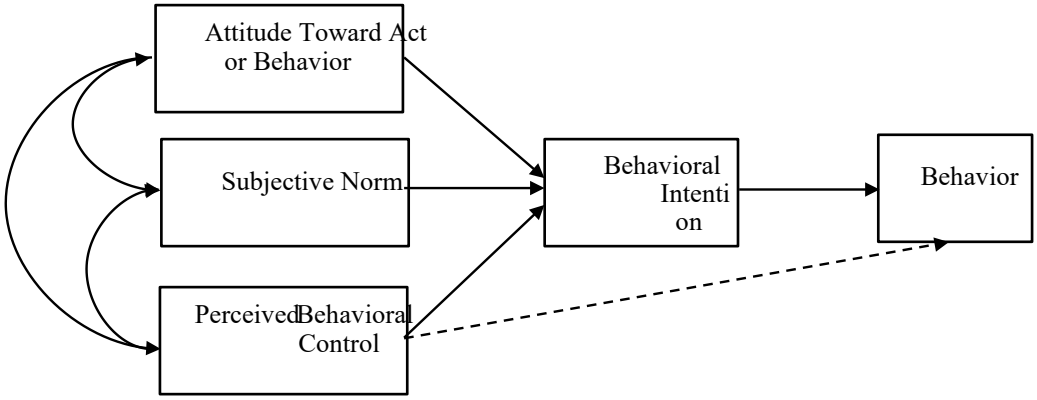


Figure 2.2
Theory of Planned Behaviour
Source: Ajzen (1991)

2.10.3 The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Fred Davis in 1989, is a theoretical model designed to explain and predict users' acceptance of IT. TAM is based on the Theory of Reasoned Action (TRA) but specifically focuses on how external factors influence users' intentions and actual use of technology. The core components of TAM are perceived usefulness (PU) and perceived ease of use (PEOU), as shown in Figure 2.3.

Perceived usefulness refers to the degree to which a person believes that using a particular system would enhance their job performance (Davis, 1989). If users perceive that a technology will help them perform their tasks more effectively, they are more likely to adopt it. Perceived ease of use, on the other hand, is the degree to which a person believes that using the system will be free of effort (Davis, 1989). Technologies that are perceived as easy to use are more likely to be accepted by users. Both PU and PEOU directly influence users' attitudes toward using the technology, which in turn affects their behavioral intentions and actual usage (Venkatesh & Davis, 2000).

Universiti Utara Malaysia

TAM has been widely applied in various fields to study the adoption of different technologies, including healthcare systems, e-learning platforms, and mobile applications (King & He, 2005). Its simplicity and strong predictive power have made it a popular choice for researchers studying technology acceptance.

Despite its strengths, TAM was excluded from this study for several reasons. Firstly, TAM focuses primarily on individual users' acceptance of technology, which does not fully capture the complexity of organisational decision-making processes involved in adopting BD technologies in SMEs (Venkatesh et al., 2012). Organisational adoption often involves multiple stakeholders and considers a broader range of factors beyond individual perceptions. Secondly, TAM does not adequately address the technological, organisational, and environmental contexts that are critical in understanding the adoption of BD technologies (Venkatesh & Bala, 2008). Lastly, while TAM is effective for studying individual technology acceptance, it lacks the comprehensive scope needed for examining the multi-faceted nature of organisational technology adoption (Venkatesh et al., 2012). Therefore, the TOE framework, which includes a more holistic view of the factors influencing technology adoption, was deemed more appropriate for this study, as shown in Figure 2.3.

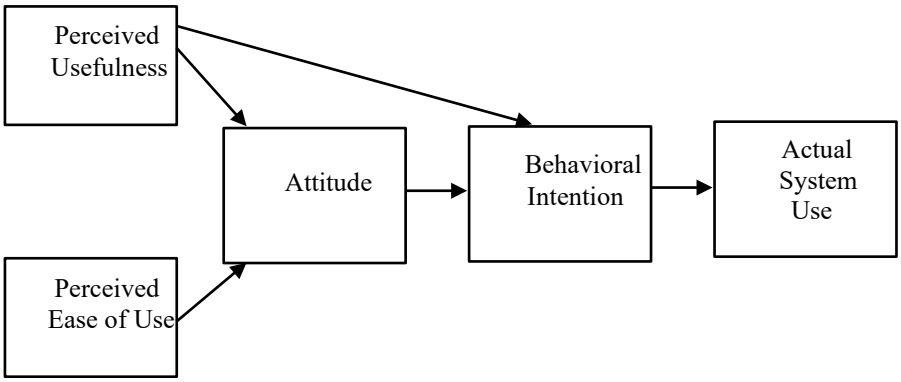


Figure 2.3
Technology Acceptance Model
Source: Davis (1989)

2.10.4 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) to explain user intentions to use an IS and subsequent usage behavior. UTAUT integrates elements from eight prominent models of technology acceptance, including the TRA, the TAM, and the TPB, among others. UTAUT posits that four key constructs performance expectancy, effort expectancy, social influence, and facilitating conditions directly determine user intention and behavior, as shown in Figure 2.4.

Performance expectancy is the degree to which an individual believes that using the technology will help them achieve gains in job performance (Venkatesh et al., 2003). Effort expectancy is the PEOU associated with technology. Social influence refers to the degree to which an individual perceives that important, others believe they should use technology. Facilitating conditions are the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of technology.

UTAUT has been widely used in various fields to study technology adoption and has demonstrated strong predictive power in explaining user behavior (Venkatesh et al., 2012). It has been applied to contexts such as mobile banking, healthcare information systems, and e-learning platforms.

Despite its strengths, UTAUT was excluded from this study for several reasons. Firstly, UTAUT, while comprehensive, primarily focuses on individual user

Universiti Utara Malaysia

acceptance and does not fully address the complexity of organisational decision-making processes involved in adopting BD technologies in SMEs (Venkatesh et al., 2003). Organisational adoption involves multiple stakeholders and external influences that UTAUT does not adequately capture. Secondly, UTAUT does not sufficiently consider the rapid technological changes and dynamic market conditions that are critical in the context of big data technology adoption. Lastly, empirical evidence suggests that while UTAUT is effective in predicting individual technology acceptance, its applicability diminishes in contexts involving complex, multi-faceted organisational decisions (Dwivedi et al., 2019). Therefore, the TOE, which provides a more holistic view of the factors influencing technology adoption, was deemed more appropriate for this study, as shown in Figure 2.4.

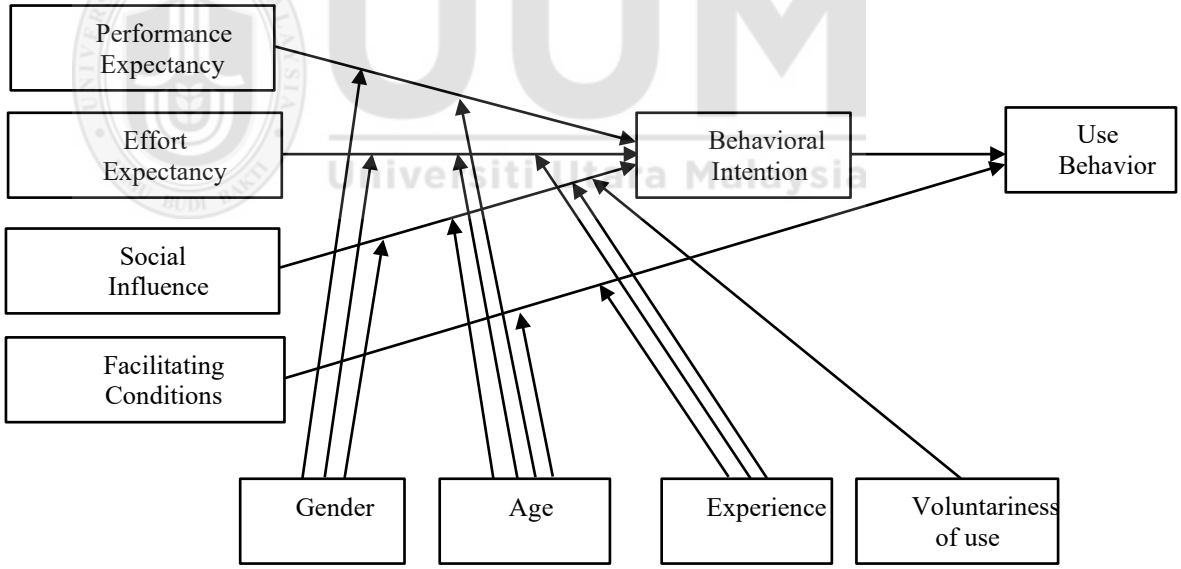


Figure 2.4
UTAUT Model
Source: Venkatesh et al. (2003)

2.10.5 Diffusion of Innovation Theory (DOI)

The Diffusion of Innovation theory, developed by Everett Rogers in 1962, explains how, why, and at what rate new ideas and technologies spread through cultures. Rogers identifies five stages in the innovation-decision process: knowledge, persuasion, decision, implementation, and confirmation. This process begins when individuals become aware of an innovation and proceed through various stages to decide whether to adopt or reject it. According to Rogers (1995), the adoption of innovations is influenced by factors such as RADV, COMP, CMPLX, TR, and OB, as shown in Figure 2.5.

RADV refers to the degree to which an innovation is perceived as better than the idea it supersedes. COMP is the extent to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters. CMPLX involves the degree to which an innovation is perceived as difficult to understand and use. TR is the extent to which an innovation can be experimented with on a limited basis, and OB is the degree to which the results of an innovation are visible to others.

DOI theory is particularly useful in studying the adoption of BD technologies in organisations. It provides a comprehensive framework to understand how BD innovations are communicated and adopted over time within social systems. For instance, Maduku et al. (2016) utilized DOI to estimate and predict the success of new technologies by examining their diffusion principles. Researchers like Wejnert (2002) have used DOI to examine determinants affecting the perception, recognition, and adoption of innovations across various social entities, including organisations.

Universiti Utara Malaysia

Several studies have applied DOI to the context of BDA. For example, Cegielski et al. (2012) investigated cloud computing adoption in SMEs using DOI and highlighted how factors like RADV and CMPLX influenced the adoption process. Similarly, Lin and Chen (2012) explored the adoption of IT innovations and confirmed the relevance of DOI in understanding the diffusion process.

In this research, the DOI theory is employed to understand the adoption of BD technologies among Palestinian SMEs. The theory's focus on innovation characteristics and the social system's influence on adoption decisions aligns well with the objectives of this study. It helps in identifying critical factors that affect the adoption process, such as the perceived advantages of BD, its COMP with existing systems, and the CMPLX involved in its implementation. The DOI theory's comprehensive approach to studying innovation diffusion makes it an appropriate framework for this research, providing valuable insights into the factors driving BDA in SMEs (Abulehia et al., 2023).

Universiti Utara Malaysia

Numerous studies have utilized the DOI theory to understand the adoption of BD technologies across different contexts. For instance, Maduku et al. (2016) applied DOI to predict the adoption of new technologies and emphasized the significance of RADV and CMPLX in this process. Similarly, Cegielski et al. (2012) used DOI to study cloud computing adoption in SMEs, identifying critical factors such as RADV and COMP.

In Palestine, Abulehia et al. (2023) conducted a study using DOI to understand the IABD among Palestinian manufacturing SMEs. Their research highlighted the importance of factors like RADV, COMP, and CMPLX, as well as OR and EXSUPP, in influencing adoption decisions. This study employed surveys with owners or

managers of 310 SMEs, demonstrating the practical application of DOI in a real-world context.

In Jordan, Lutfi et al. (2022b) utilized DOI alongside the TOE framework to investigate BDA in Jordanian manufacturing SMEs. Their findings underscored the relevance of DOI factors such as RADV and CMPLX, in addition to organisational and environmental factors like TMS and GOVS.

These studies illustrate the widespread applicability of the DOI theory in understanding BDA across different industries and regions, reinforcing its value as a theoretical framework for analysing technological diffusion and adoption processes, as shown in Figure 2.5.

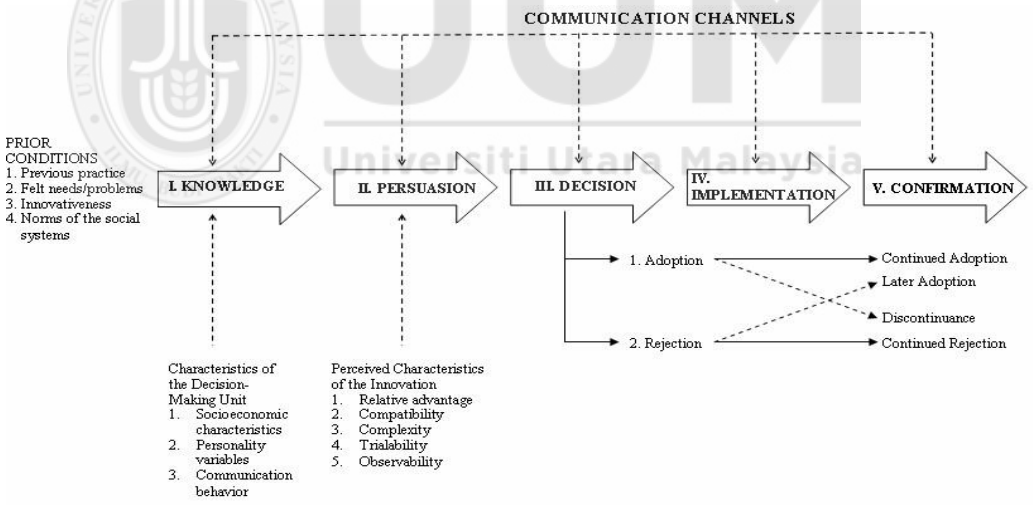
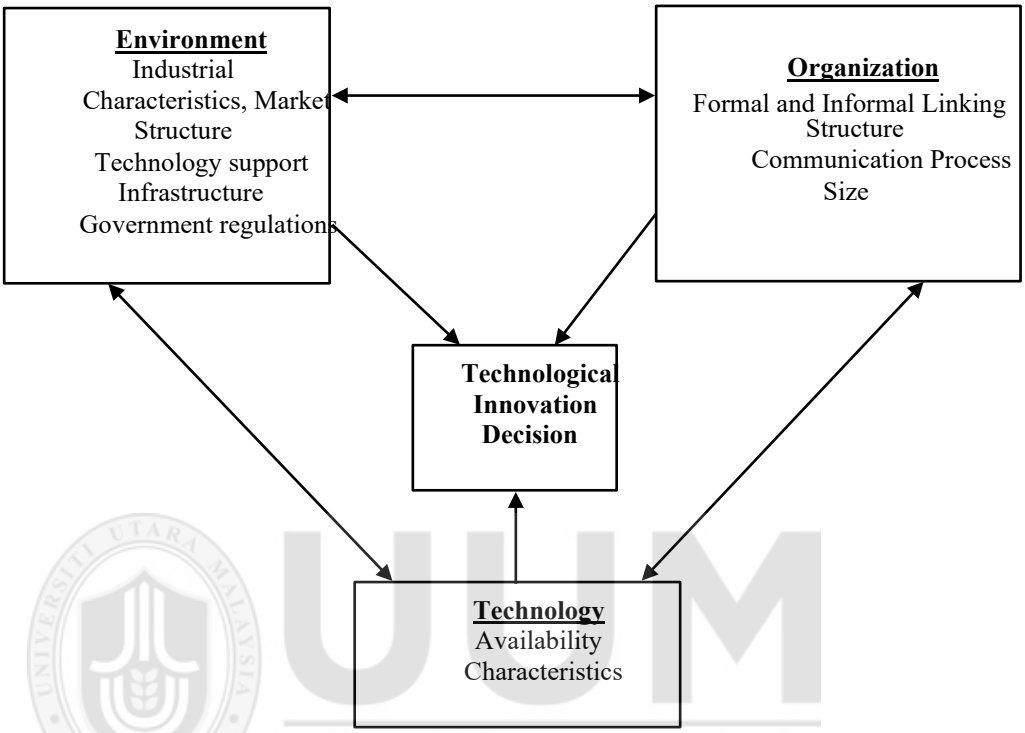


Figure 2.5
Model of Stages in the Innovation-Decision Process
Source: (Rogers, 2003)

2.10.6 The Technology-Organization-Environment (TOE)

The Technology-Organization-Environment framework, developed by Tornatzky and Fleischer, is a widely used model for understanding and predicting the adoption and

usage of technology within organisations. This model examines the impact of internal factors, such as an organisation's structure and the technology itself, along with external environmental factors on the adoption of IT, as shown in Figure 2.6.



Universiti Utara Malaysia

Figure 2.6
Technology-Organization-Environment Framework
Source: Tornatzky and Fleischer (1990)

The versatility of the TOE model has led to its application in various IT innovation scenarios across different regions. For example, it has been used to study the adoption of social media in Australian local governments (Mohd Sharif et al., 2016) and in Ghanaian SMEs (Amoah et al., 2023). Additionally, the model has been employed to analyze cloud computing adoption in Malaysian SMEs (Hassan, 2017) and Indonesian MSMEs (Aligarh et al., 2023). It has also been used to study the assimilation of ERP systems in Chinese firms (Xu et al., 2017) and ERP adoption in Nigerian SMEs (Awa et al., 2016). Further applications include investigating e-commerce adoption among Malaysian SMEs (Tamin & Adis, 2022), ICT adoption in SMEs in Bangladesh

(Shahadat et al., 2023), CRM adoption in Iranian SMEs (Forootani et al., 2022), mobile banking in Sudanese microfinance institutions (Ammar & Ahmed, 2016), and business intelligence usage in Thai SMEs (Boonsiritomachai et al., 2016). These studies highlight the model's effectiveness in understanding technology adoption trends across various industries and locations.

2.10.6.1 Rationale for Using the TOE Framework

The decision to employ the TOE framework in this study is well-supported for several reasons. Firstly, the TOE framework is widely recognized as the most extensively used theory for technology adoption, making it highly suitable for studying SMEs and offering valuable insights to address their unique challenges (Ghazi Naji et al., 2022). Unlike the Innovation Diffusion Theory, the TOE framework considers the environmental context, making it superior for analyzing innovation adoption within organisations (Lai et al., 2018). It effectively explores how technological, organisational, and environmental factors influence technology adoption decisions and company performance. Moreover, the TOE model allows for flexibility, permitting researchers to include or exclude contextual factors as needed (Grant & Yeo, 2018). Lastly, it provides a solid empirical and theoretical foundation for organisational-level studies.

Drawing on the TOE framework, this study proposes a comprehensive model to assess the influence of various factors on the IABD within SMEs. The model incorporates elements from the technological context, such as RADV, COMP, CMPLX, TR, and OB, as well as factors from the organisational context, including TMS and OR. Additionally, it considers environmental context factors such as

Universiti Utara Malaysia

COPMR, and GOVS. Contrary to the assumption of independence among TOE factors, the study introduces INNOV as a moderating variable between BDA intention and its predictors. This approach seeks to provide a more nuanced and insightful understanding of the BDA process within SMEs.

The TOE framework has demonstrated its applicability in various contexts, making it an invaluable tool for examining technology adoption. For instance, the adoption of social media in Australian local governments was studied using the TOE model, highlighting how OR and external pressure influence adoption decisions (Mohd Sharif et al., 2016). In Ghana, Amoah et al. (2023) applied the TOE framework to understand the factors driving social media adoption among SMEs, emphasizing the role of technological attributes and COPMR.

In Malaysia, the adoption of cloud computing in SMEs was analysed using the TOE framework, where Hassan (2017) found that TMS and perceived benefits were critical factors. Similarly, Aligarh et al. (2023) used the TOE model to study cloud computing adoption in Indonesian MSMEs, identifying significant factors such as OR and environmental support.

The TOE framework was also used to investigate the assimilation of ERP systems in Chinese firms, with Xu et al. (2017) demonstrating the importance of technological and organisational factors. In Nigeria, Awa et al. (2016) explored ERP adoption in SMEs, showing that external environmental factors, such as GOVS and vendor influence, played crucial roles.

These examples illustrate the TOE framework's broad applicability and effectiveness in understanding various aspects of technology adoption across different regions and

Universiti Utara Malaysia

industries. By leveraging the comprehensive nature of the TOE model, this study aims to provide a detailed and nuanced understanding of BDA in SMEs, considering the unique challenges and factors influencing this process.

2.10.7 Integration of Innovation Theory (DOI) and TOE Frameworks

The integration of the DOI theory and the TOE framework offers a comprehensive approach to understanding technology adoption within organisations. The DOI theory, proposed by Rogers (2003), emphasizes the technological attributes that drive innovation diffusion, such as RADV, COMP, and CMPLX. Meanwhile, the TOE framework, developed by Tornatzky and Fleischer (1990), extends this by incorporating organisational and environmental contexts, thus providing a broader perspective on adoption processes.

This integration covers a wide range of factors influencing technology adoption. The DOI theory focuses on the characteristics of the innovation itself, which helps in understanding the technological determinants. The TOE framework adds depth by including organisational factors such as TMS and OR, and environmental factors such as COPMR and GOVS. This combined approach allows for a more nuanced analysis of how internal and external factors interact to influence adoption decisions.

Several studies have utilised this integrated approach to study BDA. For instance, Lutfi et al. (2022b) applied both DOI and TOE frameworks to examine BDA in Jordanian manufacturing SMEs, highlighting the importance of technological factors like RADV and COMP, as well as OR and EXSUPP. Similarly, Jang et al. (2019) investigated the intention to introduce BD using both frameworks, focusing on the combined effects of technological attributes and environmental context.

The decision to integrate these two frameworks in this study is driven by the need to address the limitations of using a single theoretical model. The DOI theory alone does not account for the broader organisational and environmental influences that are crucial in the context of SMEs. Conversely, the TOE framework, while comprehensive, can benefit from the detailed insights into technological attributes provided by DOI. This integrated approach not only enhances the explanatory power but also provides a robust framework for analysing complex adoption processes, making it particularly suitable for studying BDA in SMEs.

2.11 Chapter Summary

This chapter provided a critical review of the literature on BDA and IABD among SMEs, structured around the TOE and DOI frameworks. It examined the technological, organisational, and environmental factors influencing the decision to adopt BD, emphasizing the theoretical and empirical underpinnings of each construct. The review highlighted that although BD has been extensively studied in large firms, research on SMEs remains limited, fragmented, and often contextually inconsistent. This gap is particularly evident in developing and conflict-affected economies, where firms operate under severe resource, infrastructure, and policy constraints.

The chapter identified that the ten TOE factors technological (RADV, COMP, CMPLX, TR, OB), organisational (TMS, OR), and environmental (COMPR, EXSUPP, GOVS) produce mixed results across prior studies. Such inconsistencies suggest that TOE factors alone cannot fully explain the variation in IABD outcomes. The literature therefore points to the need for additional explanatory mechanisms that account for internal heterogeneity among firms.

To address this gap, INNOV was introduced as a moderating variable that potentially alters the strength and direction of the relationships between TOE factors and IABD. Theoretical evidence supports the view that innovative organisations are more proactive, flexible, and adaptive in responding to technological and environmental changes. Consequently, INNOV enhances the explanatory power of the TOE framework by capturing behavioural and strategic readiness beyond structural factors.

The integration of TOE and DOI theories offers a robust foundation for understanding the complex dynamics of BDA. While TOE explains external and internal determinants at the organisational level, DOI contributes behavioural insights through innovation attributes such as RADV, COMP, and CMPLX. This theoretical synthesis allows a more comprehensive interpretation of how SMEs assess, internalize, and act upon BDA decisions.

In summary, this chapter provided the conceptual and theoretical basis for the study's framework. It established the relevance of TOE–DOI integration and justified the inclusion of INNOV as a moderator to address the inconsistent findings in the literature. The next chapter outlines the research framework and hypothesis development, translating these theoretical insights into a testable model explaining IABD among Palestinian SMEs.

Universiti Utara Malaysia

Summary of Independent Variables Influencing Big Data Adoption in Previous Studies

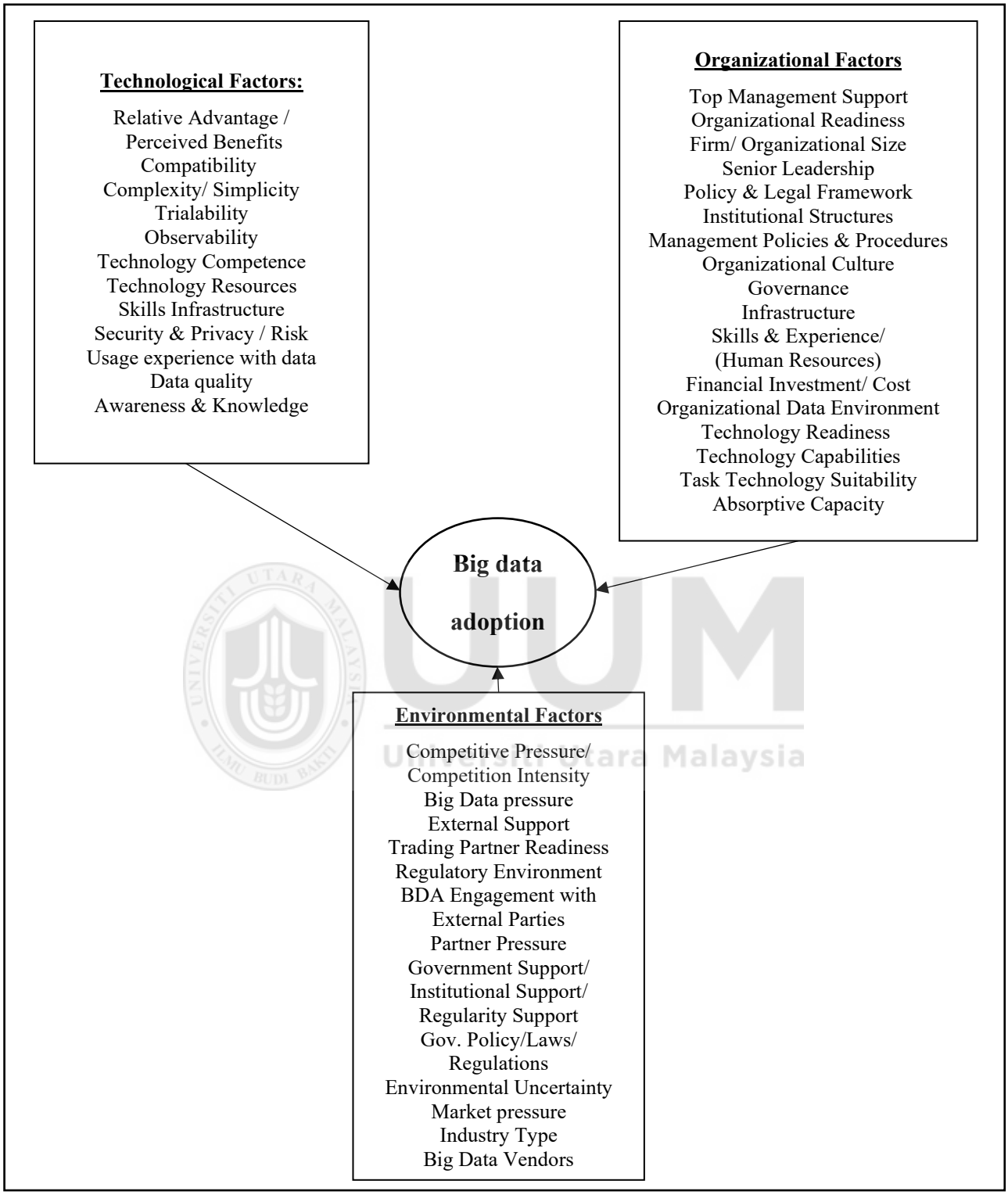


Figure 2.7
Summary of Independent Variables that Influence big data adoption Reported in Previous Research
Source: Developed by the researcher based on previous studies

Universiti Utara Malaysia

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter explained the research methodology that was employed to achieve the aims of this study. The main purpose of the research was to examine the TOE factors that influenced the IABD among SMEs in Palestine, and to test the moderating role of INNOV.

The chapter restated the focus of the study and outlined the systematic steps that were undertaken to achieve the research objectives discussed in Chapter One. It provided an in-depth explanation of the research methodology, including the research framework, research design, operational definitions, measurement of variables and instruments, questionnaire design and translation, population and sampling methods, data collection procedures, and data analysis techniques.

Universiti Utara Malaysia

By presenting these methodological components, this chapter demonstrated how the study was carefully designed and implemented to ensure reliability, validity, and alignment with the overall research aims.

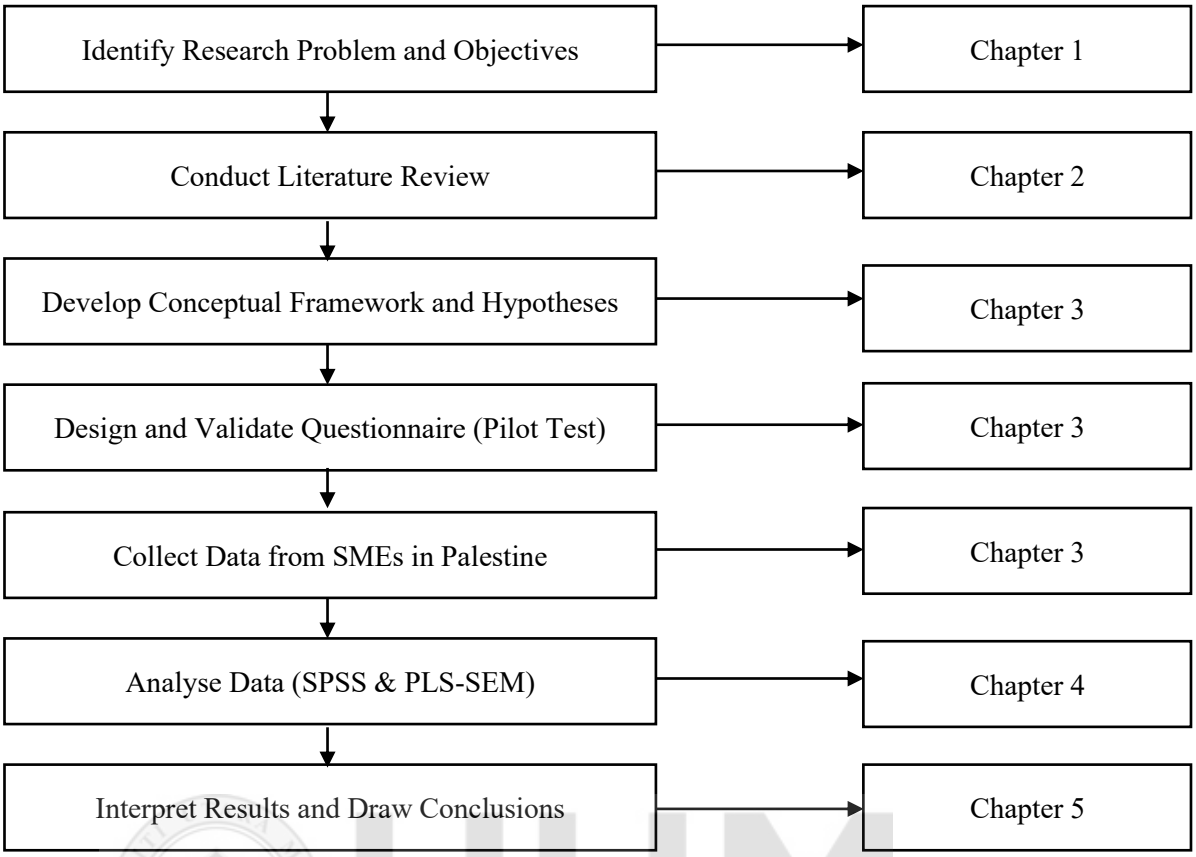


Figure 3.1
Research Process

Figure 3.1 illustrates the overall research process followed in this study. The process began in Chapter One, where the research problem and objectives were identified. Chapter Two reviewed the relevant literature and established the theoretical foundations of the study. Based on these theories, the conceptual framework and hypotheses were developed in Chapter Three. The same chapter also described the questionnaire design and pilot testing, followed by data collection from SMEs in Palestine. In Chapter Four, the collected data were analysed using SPSS and PLS-SEM to test the research hypotheses. Finally, Chapter Five presented the interpretation of results, discussion, and conclusions, providing insights and recommendations derived from the study findings.

3.2 Theoretical Framework

The research framework was developed following a thorough literature review, as

Universiti Utara Malaysia

detailed in the previous chapter. The connections illustrated in Figure 3.1 are grounded in existing literature. This research framework is constructed through prior studies and precise research findings from relevant theories and analytical models. It addresses the current research problem concerning technological, organisational, and environmental factors, INNOV, and the IABD in Palestinian SMEs. The choice of theory is based on its relevance, ease of application, and explanatory power as derived from the literature.

Based on the literature and theories discussed earlier, a research framework has been proposed for the study, as shown in Figure 3.2.

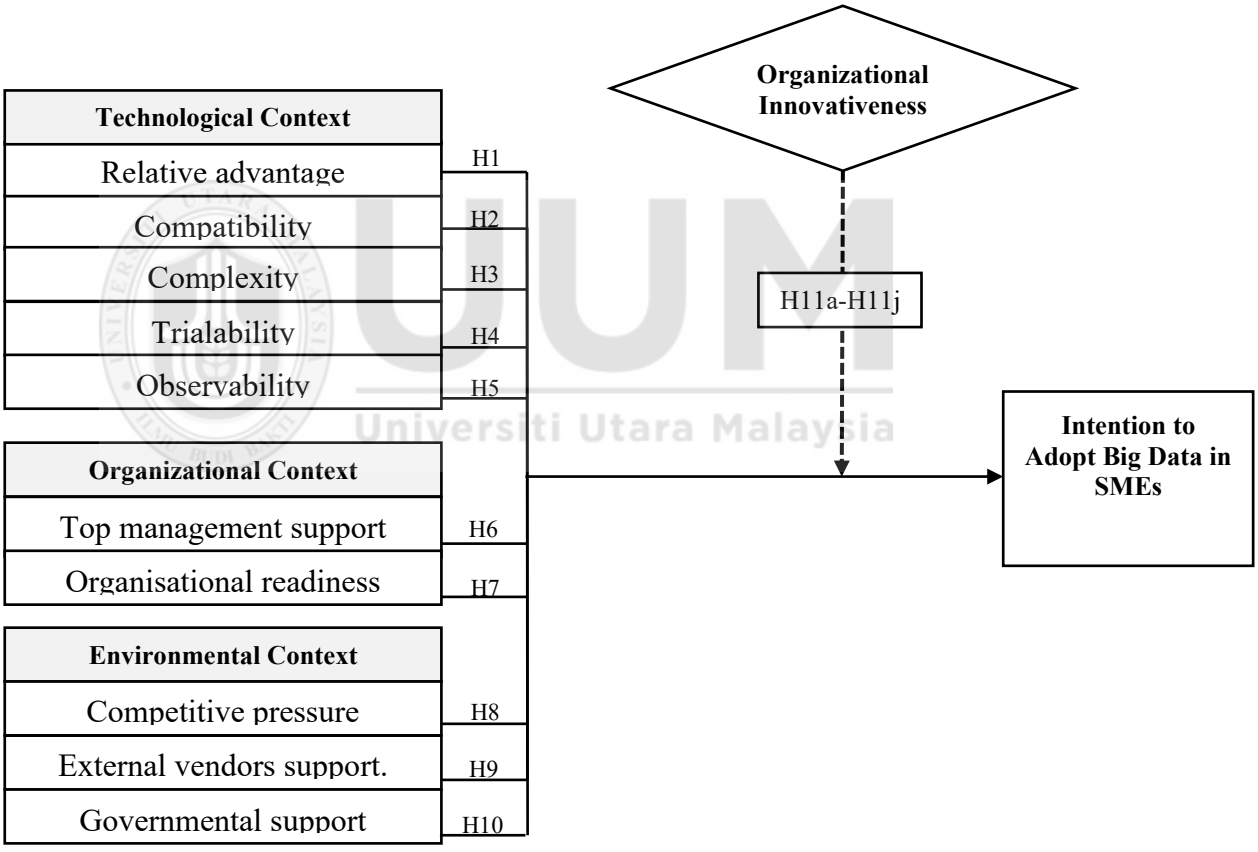


Figure 3.2
Research Framework

Universiti Utara Malaysia

Figure 3.2 represents the relationship between technological factors, organisational factors, environmental factors, INNOV, and the IABD among SMEs in Palestine. This model depicts that technological factors, organisational factors, environmental factors as independent variables (IVs), INNOV (Mod Vs), and the IABD as the dependent variable (DV).

3.3 Hypotheses Development

3.3.1 Technological Factors

3.3.1.1 Relative advantage

Relative advantage (RADV) refers to the extent to which an innovation is perceived as offering superior benefits compared to existing practices (Rogers, 2003). Prior empirical studies consistently demonstrated that the relative advantage of BD supports organisations by enhancing decision-making, real-time analytics, operational efficiency, and cost reduction (Agrawal, 2015; Mahesh et al., 2018; Sun et al., 2018).

Evidence from both developed and developing economies indicates that RADV is one of the strongest predictors of technology adoption, particularly in the context of BD initiatives among SMEs (Shin, 2016; Verma, 2017; Baig et al., 2019; Yadegaridehkordi et al., 2020; Brock & Khan, 2017).

Recent research also highlighted that SMEs are more inclined to adopt BD when they perceive clear strategic value, such as improved competitiveness, enhanced productivity, and better responsiveness to market conditions (Wahab et al., 2018). Collectively, these studies provide consistent theoretical and empirical support for the critical role of RADV in shaping behavioural intentions toward BDA.

Therefore, the following hypothesis is proposed:

H1: Relative advantage has a significant effect on the intention to adopt big data.

3.3.1.2 Compatibility

Compatibility (COMP) refers to the extent to which an innovation aligns with an organisation's existing values, prior experiences, and operational needs (Rogers, 2003). In the context of BD, COMP reflects how well BD applications fit with current IS, business processes, and organisational culture (Agrawal, 2015). Prior studies emphasised that SMEs are more likely to adopt new technologies when these technologies integrate smoothly with existing infrastructures and do not require major structural or cultural changes (Verma & Chaurasia, 2019; Jang et al., 2019).

Empirical evidence shows that when BD solutions share similar technological architectures with current IT systems, organisations perceive lower implementation barriers and greater strategic value, which increases their intention to adopt such innovations (Maroufkhani et al., 2020a; Verma & Chaurasia, 2019). Although some studies have reported mixed results regarding COMP and BDA, broader research on innovation adoption continues to identify COMP as a significant facilitator of technology acceptance, especially among SMEs where resources and IT expertise are limited (Wang et al., 2010; Ghobakhloo et al., 2011).

Overall, COMP influences whether organisations view BD as a natural extension of their existing capabilities, which in turn shapes their intention to adopt it. Based on this theoretical and empirical evidence, the following hypothesis is proposed:

H2: Compatibility has a significant effect on the intention to adopt big data.

3.3.1.3 Complexity

Complexity (CMPLX) refers to the degree to which an innovation is perceived as difficult to understand or use (Rogers, 2003; Lee, 2004). Prior research indicated that when a technology is seen as technically challenging or requires substantial new skills, users are less likely to adopt it (Chen et al., 2015). For SMEs in particular, complex technologies often create operational disruptions, increase uncertainty, and require changes to existing processes, which may delay or discourage adoption decisions (Maroufkhani et al., 2020a).

In the context of BD, CMPLX emerges from its technical characteristics, including large-scale data processing, specialized tools such as Hadoop and Spark, advanced analytics, and the need for mathematical and programming expertise (Gangwar, 2018). These requirements may exceed the capabilities of many SMEs, leading to concerns about implementation difficulties and resource constraints. Nonetheless, CMPLX has traditionally been recognized as a core factor affecting innovation adoption across multiple contexts (Premkumar & Roberts, 1999).

However, empirical evidence regarding the effect of CMPLX on BDA remains inconsistent. While some studies reported a negative association between perceived difficulty and BDA (Gangwar, 2018), others found that CMPLX does not significantly influence adoption decisions, especially in service-oriented firms (Ramdani et al., 2009; Alshamaila et al., 2013; Tsai et al., 2010; Jang et al., 2019). These mixed findings suggest that the role of CMPLX may depend on contextual factors such as industry type, OR, and access to external expertise.

Despite these inconsistencies, CMPLX remains an important attribute within innovation adoption theory, particularly under DOI, and may shape SMEs' IABD when perceived technical barriers are high. Based on this theoretical justification, the following hypothesis is proposed:

H3: Complexity has a significant effect on the intention to adopt big data.

3.3.1.4 Trialability

Trialability (TR) refers to the extent to which an innovation can be tested or experimented with before full adoption (Priyadarshinee et al., 2017). Within the DOI framework, TR reduces uncertainty by allowing organisations particularly SMEs to evaluate the usefulness, COMP, and operational implications of a new technology on a limited scale. The opportunity to experiment helps firms form clearer expectations about potential benefits and challenges, thereby supporting more informed adoption decisions.

Universiti Utara Malaysia

Empirical studies across various technologies have demonstrated the importance of TR in shaping organisational behaviour. For example, Alshamaila et al. (2013) found that the ability to test cloud computing solutions significantly increased adoption among SMEs. In the context of BD, recent evidence shows that TR influences adoption decisions in different sectors, including tourism, hospitality, and manufacturing (Sharma et al., 2023; Yadegaridehkordi et al., 2018). Although the strength of this influence varies across industries, the availability of trial features consistently supports early-stage evaluation and reduces perceived risks.

For SMEs, TR is particularly valuable because it addresses concerns about technical

CMPLX, resource limitations, and the potential disruption associated with new technologies. Allowing SMEs to experience BD tools in a controlled environment helps them assess operational fit and expected outcomes, which can mitigate adoption barriers related to uncertainty and lack of expertise (Maroufkhani et al., 2020b). Conversely, the absence of such opportunities may increase perceived risk and discourage adoption.

Based on the theoretical rationale and empirical evidence, the following hypothesis is proposed:

H4: Trialability has a significant effect on the intention to adopt big data.

3.3.1.5 Observability

Observability (OB) refers to the extent to which the outcomes and benefits of an innovation are visible to others (Rogers, 2003). In the context of BD, OB enables SMEs to witness how similar organisations have successfully implemented BD solutions and how these technologies contribute to improved performance. This visibility reduces uncertainty, builds confidence, and supports more informed adoption decisions.

Previous studies have highlighted the influential role of OB in technology adoption. Maroufkhani et al. (2020) noted that when SMEs can observe clear examples of BD usage, perceived risks decline and willingness to adopt increases. Empirical evidence from Malaysian manufacturing firms also demonstrated that OB significantly shapes adoption intentions, as organisations tend to rely on visible success stories when evaluating complex technologies (Yadegaridehkordi et al., 2018). Likewise, research

in sectors such as banking and healthcare found that visible benefits and demonstrable outcomes of BD systems strongly motivate adoption decisions (Verma & Bhattacharyya, 2017).

For SMEs, OB serves an important bridging function. By providing practical demonstrations of how BD can enhance decision-making, operational efficiency, and competitiveness, OB helps mitigate concerns about technical CMPLX and resource requirements. Studies further indicate that peer influence and industry trends amplify this effect: when leading or competing firms visibly adopt BD tools, others are more likely to follow due to COMPR and the desire to benefit from similar outcomes (Lu et al., 2009).

Overall, the literature consistently shows that observable results play a significant role in shaping SMEs' perceptions of BD technologies and reducing uncertainty surrounding adoption. Based on this theoretical and empirical grounding, the following hypothesis is proposed:

Universiti Utara Malaysia

H5: Observability has a significant effect on the intention to adopt big data.

3.3.2 Organisational Factors

3.3.2.1 Top Management Support

Top Management Support (TMS) refers to the extent to which senior leaders recognise the value of an innovation and provide the necessary guidance, resources, and commitment to enable its adoption (Ramdani & Kawalek, 2008). When top managers believe that adopting new technologies will generate strategic or operational benefits,

they are more likely to allocate financial and human resources, reduce internal resistance, and foster a supportive environment for implementation (Thong, 1999). This support helps shape organisational culture and encourages employees to engage with emerging technologies (Premkumar & Roberts, 1999).

Within the context of BDA, empirical research consistently highlights the importance of TMS. Studies indicate that firms with strong leadership commitment show higher readiness for technological change and are more willing to experiment with and adopt BD solutions (Park & Kim, 2021; Gangwar, 2018). For instance, Verma and Chaurasia (2019) reported that TMS significantly influenced BDA among adopters, although its effect was weaker among non-adopters. Additionally, Lai et al. (2018) showed that leadership support directly enhances behavioural intention toward adopting BD technologies.

Top management plays a critical role in addressing challenges associated with BD implementation, such as system integration, reengineering processes, staff training, and cross-departmental coordination. As BD initiatives often require organisational adjustments and investment in new capabilities, leadership commitment ensures that these changes are prioritised and effectively managed.

Based on this theoretical and empirical foundation, the following hypothesis is proposed:

H6: Top management support has a significant effect on the intention to adopt big data.

Universiti Utara Malaysia

3.3.2.2 Organisational Readiness

Organisational readiness (OR) refers to the extent to which an organisation possesses the financial resources, technical capabilities, and human competencies required to implement new technologies (Gangwar, 2018; Yoon & George, 2013). It reflects both the organisation's preparedness and its willingness to invest in emerging innovations such as BD analytics. Prior studies have noted that readiness including adequate IT infrastructure, skilled personnel, and strategic capabilities is a prerequisite for successful technology adoption, particularly in resource-constrained SMEs (Taxman et al., 2014).

Empirical research consistently supports the significant role of OR in technology adoption decisions. Studies on SMEs demonstrated that firms with higher levels of financial, technical, and human resource readiness are more likely to adopt innovations, including BD solutions (Ghobakhloo, 2011; Asiaei & Ab. Rahim, 2019). These findings are aligned with earlier technology adoption literature, which emphasised that insufficient resources and limited internal capabilities hinder the adoption of advanced technologies among SMEs (Ramdani et al., 2013).

Universiti Utara Malaysia

In the context of BD, readiness is particularly important due to the complexity of data infrastructure, the need for specialised analytical skills, and the investment required to integrate BD tools into existing systems. Without sufficient readiness, SMEs may struggle to support implementation or sustain BD initiatives, making adoption unlikely. Conversely, when organisations demonstrate strong managerial commitment, adequate resources, and skilled personnel, they are better positioned to engage with BD technologies (Jang et al., 2019; Sun et al., 2020; Mneney & Belle, 2016).

Based on this theoretical and empirical evidence, the following hypothesis is proposed:

H7: Organisational readiness has a significant effect on the intention to adopt big data.

3.3.3 Environmental Factors

In the current study, COMPR, EXSUPP and GOVS are the environmental factors, as a combined environmental perspective, which affects BDA among SMEs in Palestine.

3.3.3.1 Competitive pressure

Competitive pressure (COMPR) refers to external forces such as competitors, customers, and suppliers that compel organisations to adopt new technologies in order to remain competitive (Oliveira et al., 2014). In open and dynamic markets, firms often respond to competitors' technological advancements to avoid losing customers or market position. When rival firms implement BD technologies, this visible shift increases the pressure on others to follow in order to sustain performance and competitive advantage (Sun et al., 2020).

Universiti Utara Malaysia

Empirical studies consistently demonstrate that COMPR is a key driver of BDA across sectors and economic contexts. Research from India, Malaysia, and other developing economies found that firms experiencing stronger competition were more inclined to integrate BD tools to improve decision-making, operational efficiency, inventory visibility, customer understanding, and overall productivity (Verma & Chaurasia, 2019; Gangwar, 2018; Yadegaridehkordi et al., 2018). These studies also show that COMPR influences both adopters and non-adopters, indicating its wide-reaching effect on organisational decisions.

However, findings on the influence of COMPR remain mixed. Some studies reported that COMPR did not significantly affect BDA, particularly in contexts where internal organisational factors such as readiness, management support, or resource availability played a more dominant role (Maroufkhani et al., 2020a; Park & Kim, 2021; Schüll et al., 2018). This variation suggests that the effect of COMPR may depend on industry characteristics, market maturity, and organisational capabilities.

Despite these inconsistencies, COMPR continues to be recognised as an important environmental factor within the TOE framework, particularly for SMEs seeking to remain competitive in rapidly changing digital environments.

Based on this theoretical and empirical evidence, the following hypothesis is proposed:

H8: Competitive pressure has a significant effect on the intention to adopt big data.

Universiti Utara Malaysia

3.3.3.2 External Vendors Support

External Vendors Support (EXSUPP) refers to the assistance provided by technology vendors or third-party consultants that enables organisations to adopt and integrate innovations such as BD (Gangwar, 2018). SMEs often face shortages in technical expertise, analytical skills, and infrastructure readiness; therefore, EXSUPP becomes an essential mechanism to overcome capability gaps and reduce implementation risks (Maroufkhani et al., 2020b).

Prior studies emphasised that SMEs lacking in-house BD skills rely heavily on external consultants to deploy, manage, and maintain BD systems effectively (Salleh & Janczewski, 2018; Mneney et al., 2016). Empirical evidence shows that EXSUPP

significantly facilitates BDA across various sectors, as external experts provide training, technical guidance, and customised solutions that lower implementation barriers (Yadegaridehkordi et al., 2020; Gangwar, 2018). In both manufacturing and service industries, EXSUPP has been found to positively influence organisational decisions to adopt BD technologies (Gangwar, 2018).

However, evidence is not entirely consistent. Mneney et al., (2016) reported an insignificant effect of EXSUPP on BDA, suggesting that its influence may depend on OR or industry context. Despite these mixed findings, the literature generally recognises EXSUPP as a key environmental factor that reduces uncertainty and enhances SMEs' confidence in adopting complex technologies.

Based on the theoretical and empirical insights, the following hypothesis is proposed:

H9: External vendor support has a significant effect on the intention to adopt big data.

Universiti Utara Malaysia

3.3.3.3 Governmental Support

Government support (GOVS) refers to the extent to which public policies, incentives, training programmes, and regulatory frameworks encourage organisations to adopt new technologies. In the context of BDA, government interventions such as financial assistance, technical training, and supportive digitalisation policies can play a critical role in reducing uncertainty and facilitating OR, particularly among SMEs.

Empirical studies widely acknowledge that GOVS is an important predictor of BDA (Sun et al., 2020; Park & Kim, 2021; Jang et al., 2019; Lai et al., 2018; Wang et al., 2018). These studies emphasise that government-led initiatives can lower adoption

barriers by providing access to expertise, developing digital infrastructure, and offering incentives for firms to experiment with advanced technologies. For example, Park and Kim (2021) found that government policies had a relatively strong influence on adoption decisions in both manufacturing and service sectors.

However, findings in the literature are not entirely consistent. While Mahesh et al. (2018) reported a positive association between GOVS and BDA, Agrawal (2015) found a negative relationship, attributing this to insufficient governmental assistance offered to firms in emerging economies. These conflicting results suggest that the effectiveness of GOVS may vary depending on policy quality, industry structure, and national digital readiness.

Despite these mixed findings, many scholars argue that appropriate government interventions such as tax incentives, digital training programmes, and innovation-friendly regulations can substantially enhance firms' willingness to adopt BD technologies (Maroufkhani et al., 2020a).

Universiti Utara Malaysia

Based on this theoretical and empirical evidence, the following hypothesis is proposed:

H10: Government support has a significant effect on the intention to adopt big data.

3.3.4 Moderator Role of Organisational Innovativeness

Organisational Innovativeness (INNOV) represents an organisation's openness to new ideas, its capacity to embrace experimentation, and its willingness to implement novel technologies ahead of competitors. It reflects a cultural and strategic orientation toward continuous improvement, creativity, and proactive problem-solving (Rogers, 2003;

Marcati et al., 2008)

In SMEs, this characteristic is especially important because these firms often operate under resource limitations, uncertain market conditions, and evolving technological landscapes. Prior research indicates that innovative SMEs tend to be more flexible, responsive, and capable of integrating digital technologies, enabling them to adopt advanced systems such as BD analytics more readily than less innovative firms (Agarwal & Prasad, 1998; Thong, 1999; Premkumar & Roberts, 1999).

INNOV therefore serves not only as an internal capability but as a strategic driver of digital transformation. As such, it may significantly influence how SMEs interpret the importance of technological, organisational, and environmental conditions when deciding whether to adopt BD.

3.3.4.1 Technological Factors and the Moderating Role of Organisational Innovativeness

Universiti Utara Malaysia

The adoption of BD technologies presents substantial organisational and operational challenges for SMEs, including the need for technical competencies, data-driven workflows, and advanced analytical skills (Gangwar, 2018). SMEs with higher levels of innovativeness are more willing to explore such technologies, test their capabilities, and reconfigure internal processes when necessary (Agarwal & Prasad, 1998; Thong, 1999). They recognise the strategic value of data analytics, such as enhanced decision-making, operational efficiency, and competitive advantage, which encourages them to treat BD as an opportunity rather than a risk (Premkumar & Roberts, 1999). This behavior aligns with the DOI theory, which posits that organisations with greater

innovativeness are more likely to perceive innovations as beneficial, aligned with organisational needs, and compatible with their existing practices (Rogers, 2003).

Organisational innovativeness therefore shapes how SMEs assess the technological attributes identified in the TOE framework. Innovative firms tend to perceive the RADV of BD more clearly (Gangwar, 2018), recognize higher levels of COMP between BD tools and organisational processes (Alaskar et al., 2020; Baig et al., 2021), and experience fewer perceived obstacles related to complexity, as they encourage experimentation, problem-solving, and internal skill development (Chen et al., 2015; Maroufkhani et al., 2020b). Likewise, TR and OB become more influential among innovative SMEs, as they frequently test new technologies and pay closer attention to observable success stories within their industries (Lu et al., 2009; Yadegaridehkordi et al., 2018).

Taken together, INNOV amplifies the effect of all five technological factors RADV, COMP, CMPLX, TR, and OB on SMEs' IABD.

Therefore, the following hypotheses are proposed:

H11a–H11e: Organisational innovativeness moderates the relationship between technological factors (relative advantage, compatibility, complexity, trialability, and observability) and the intention to adopt big data.

Universiti Utara Malaysia

3.3.4.2 Organisational Factors and the Moderating Role of Organisational Innovativeness

A similar moderating pattern emerges within the organisational context of the TOE framework, where TMS and OR are widely recognised as essential factors influencing the innovation adoption (Lai et al., 2018; Ramdani & Kawalek, 2008). Organisations with a strong culture of innovativeness tend to experience stronger and more positive effects from leadership support because innovative leaders allocate resources more proactively, reduce internal resistance, and articulate a clear digital vision aligned with organisational transformation (Karahanna & Preston, 2013). This alignment fosters an environment in which technology adoption becomes easier to initiate and sustain.

Organisational readiness, defined through financial capacity, technical infrastructure, and human expertise (Yoon & George, 2013), also becomes more impactful in innovative SMEs. Such organisations can mobilise resources more effectively, invest in training, redesign internal processes, and build the required digital capabilities for BD implementation (Ghobakhloo, 2011; Asiaei & Ab. Rahim, 2019).

Universiti Utara Malaysia

Thus, INNOV intensifies the influence of both TMS and OR on SMEs' IABD.

Accordingly, the following hypotheses are proposed:

H11f–H11g: Organisational innovativeness moderates the relationship between organisational factors (top management support and organisational readiness) and the intention to adopt big data.

3.3.4.3 Environmental Factors and the Moderating Role of Organisational Innovativeness

Within the environmental dimension of the TOE framework, SMEs respond to external drivers such as COMPR, EXSUPP, and GOVS. Prior studies, however, report inconsistent findings regarding the influence of these environmental factors on BDA (Sun et al., 2020; Park & Kim, 2021; Maroufkhani et al., 2020b). Organisational innovativeness offers a theoretically grounded explanation for these inconsistencies.

Innovative SMEs tend to respond more strongly to COMPR because they are more sensitive to industry trends and more aware of the risks of falling behind technologically (Verma & Chaurasia, 2019; Gangwar, 2018). They also leverage EXSUPP more effectively, as innovative firms proactively seek expert guidance, technical support, and consulting services to compensate for limited internal BD expertise (Salleh & Janczewski, 2018; Yadegaridehkordi et al., 2018). Furthermore, government supporting the form of incentives, training programs, or digitalization policies becomes more impactful among INNOV that possess the cultural readiness and strategic vision required to benefit from public initiatives (Mahesh et al., 2018; Maroufkhani et al., 2020b).

Accordingly, INNOV strengthens the role of environmental factors by enabling SMEs to transform external pressures and support mechanisms into meaningful adoption behavior.

Based on this reasoning, the following hypotheses are proposed:

Universiti Utara Malaysia

H11h–H11j: Organisational innovativeness moderates the relationship between environmental factors (competitive pressure, external vendor support, and government support) and the intention to adopt big data.

Integrating INNOV as a moderating variable strengthens the theoretical connection between the TOE framework and the DOI theory. The TOE framework explains the structural, internal, and external conditions that shape technology adoption (Tornatzky & Fleischer, 1990), while DOI explains how innovation attributes and organisational characteristics such as innovativeness affect adoption behavior (Rogers, 2003). INNOV forms the conceptual link between the two frameworks by shaping how SMEs perceive technological attributes, how they mobilize internal resources, and how they respond to environmental pressures.

By moderating the relationships between TOE dimensions and the intention to adopt BD, INNOV helps explain the inconsistent findings reported in earlier research on BDA among SMEs (Park & Kim, 2021; Verma & Chaurasia, 2019). This integration offers a richer and more nuanced understanding of why similar organisations exposed to the same technological and environmental conditions may reach different adoption decisions. The combined TOE–DOI perspective therefore advances theoretical understanding and provides practical insights, showing that fostering an innovative culture can enhance the effects of TOE factors and accelerate the digital transformation journey of SMEs.

Universiti Utara Malaysia

3.4 Research Design

Research design refers to the overall plan that guides the processes of collecting, analysing, and interpreting data in a systematic and coherent manner (Zikmund et al.,

2013). It provides a structured framework that ensures the research objectives are addressed appropriately and that the procedures used are aligned with the nature of the research questions. In this study, the research design was developed to investigate the relationships between technological, organisational, and environmental factors and the IABD among SMEs in Palestine, as well as to examine the moderating role of INNOV on these relationships.

Given the purpose of the study, a descriptive, hypothesis-testing, and explanatory research design was adopted. The descriptive component allows for identifying and characterizing the current state of BDA among SMEs, while the hypothesis-testing element supports the evaluation of theoretical relationships derived from the TOE framework and the DOI theory. The explanatory dimension provides insight into the causal relationships among variables, particularly the mechanisms through which INNOV influences the strength of these associations. Such a combined approach is widely used in technology adoption research, offering a comprehensive understanding of both the "what" and the "why" behind the adoption process.

To collect data relevant to the conceptual model, a quantitative survey method was employed. This method is appropriate for studies requiring generalisable findings and statistical examination of relationships between constructs (Ishtiaq, 2019). An online survey using Google Forms served as the primary data collection tool due to its efficiency, accessibility, and suitability for reaching respondents across different geographical locations. To enhance the response rate and include SMEs with limited digital access, printed questionnaires were also distributed manually. This mixed mode of distribution helped ensure better coverage and increased the likelihood of obtaining a more representative sample.

A cross-sectional research design was used, where data were collected at a single point in time from participating SMEs (Cavana et al., 2001). A cross-sectional approach is appropriate for examining the structural relationships among variables in a stable time frame and is consistent with many prior studies on technology adoption. It offers practical advantages such as reduced time, fewer resources, and quicker data collection compared to longitudinal designs. Although cross-sectional studies cannot establish temporal causality, they are effective for testing theoretically grounded models such as those developed from the TOE and DOI frameworks.

Overall, the selected research design aligns strongly with the study's objectives. It allows for rigorous empirical testing of the proposed hypotheses, supports the examination of moderating relationships, and enables the development of meaningful insights into the factors influencing of BDA among SMEs in Palestine.

Universiti Utara Malaysia

3.4.1 Nature of the study

Exploratory, analytical, or hypothesis-testing approaches can be used for analysis. Exploratory studies aim to investigate new fields of science, while descriptive analysis seeks to explain specific features of a phenomenon. Hypothesis-testing research, on the other hand, focuses on examining differences in dependent variables (Sekaran & Bougie, 2016). The type of study conducted depends on the research purpose. Since this research aims to predict the factors that significantly influence an organisation's IABD in SMEs, it can be classified as a hypothesis-testing study.

3.4.2 Unit of Analysis

The unit of analysis refers to what is being studied for variable measurements

(Neuman, 2005). In this study, SMEs are taken as the unit of analysis, with the owners or managers representing their respective firms. Data will be collected from the owners and managers of SMEs in Palestine, as they are considered key decision-makers regarding IT, BD, and innovation adoption (Gangwar, 2018). They are expected to have comprehensive knowledge of their companies' existing IT activities and future developments. Therefore, they are well-positioned to provide insightful responses to the questionnaire, representing their firms' technological, organisational, and environmental factors, as well as their INNOV and IABD (Maroufkhani et al., 2020a).

3.4.3 Research Approach

In social science research, two main philosophical paradigms are commonly discussed: positivism and interpretivism. Positivism assumes that reality is objective and can be measured through observable and quantifiable facts. Researchers following this paradigm rely on structured methods, statistical analysis, and hypothesis testing to explain causal relationships between variables (Collis & Hussey, 2003; Saunders et al., 2009).

Universiti Utara Malaysia

In contrast, interpretivism focuses on understanding social phenomena from the perspectives and meanings of individuals. It emphasizes qualitative inquiry, subjective interpretation, and context-specific insights rather than universal laws (Easterby-Smith et al., 2008).

As this study aimed to test established theories (TOE and DOI) and examine measurable relationships among variables using quantitative data, it was conducted under the positivist paradigm. This paradigm supports objective measurement and hypothesis testing, making it the most appropriate philosophical foundation for this

research.

Aligned with the positivist paradigm, the research approach for this study is deductive, which involves "theory testing." The deductive process begins with an established theory, leading to the development of hypotheses. This is followed by data collection and a summary of results where the hypotheses are either supported or rejected, culminating in the revision of the theory. In a deductive approach, conclusions are drawn through logical reasoning, starting from a known premise or something considered true (Ghauri & Gronhaug, 2005). In summary, by employing a deductive approach, this study developed a theory and hypotheses, and designed a research strategy to test these hypotheses (Saunders et al., 2009). Survey questionnaires are commonly used for data collection in research utilizing the deductive approach (Saunders et al., 2009).

Universiti Utara Malaysia

An alternative research approach is the inductive, or "theory-building," method, which is associated with the constructivist paradigm. In this approach, theory is developed from empirical observations or reality (Saunders et al., 2009). Research using an inductive approach begins with data collection, followed by data analysis, and ultimately, theory is formed from these data. Collis and Hussey (2003) describe the inductive approach as theory-building, moving from specific observations to general laws or patterns. However, the researcher's explanation may be prone to bias or misinterpretation, potentially affecting the research findings. Easterby-Smith et al., (2008) note that this approach is typically used when there is little or no prior knowledge about a specific topic, making it difficult to form hypotheses, as shown in Figure 3.3.

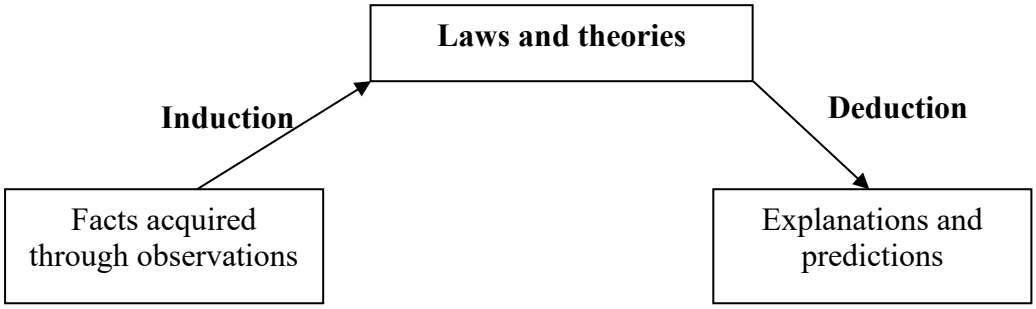


Figure 3.3
Deductive and Inductive Approaches
Source: Adapted from Saunders et al. (2009)

3.4.4 Population and Sample Frame

Sekaran (2003) suggests that a community consists of numerous individuals, incidents, and points of interest that a researcher may focus on. A sample is a subset of the population selected for study. The survey includes participants who are chosen from this selected population.

Universiti Utara Malaysia

3.4.4.1 Population of Study

This study will be conducted among Palestinian SMEs, specifically focusing on owner-managed SME firms located in the Gaza Strip, including North Gaza, Gaza City, Deir Al-Balah, Khan Yunis, and Rafah. According to the comprehensive census conducted by the PCBS in 2017, there are a total of 158,590 enterprises in Palestine, with 50,102 located in the Gaza Strip. These businesses employ 134,238 individuals in the Gaza Strip alone. SMEs represent approximately 98.4 percent of all operational organisations in Palestine.

SMEs in Palestine operate across various sectors, including manufacturing Industry, Construction, Trade, and Services. The Palestinian government classifies enterprises

into three types based on size and turnover: microenterprises, small enterprises, and medium enterprises. Microenterprises have 1-4 employees with an annual turnover of less than 20,000 USD. Small enterprises have 5-9 employees and an annual turnover of less than 200,000 USD. Medium enterprises have 10-19 employees with an annual turnover of less than 500,000 USD.

To ensure that the study's findings can be generalized across all sectors of SMEs in Palestine, a sample will be taken from each sector. This approach will provide a comprehensive representation of the study population and allow for more accurate and applicable results across various SME sectors.

This study employed a stratified random sampling technique. The sample was stratified based on two main criteria: the five governorates of the Gaza Strip (North Gaza, Gaza City, Deir Al-Balah, Khan Yunis, and Rafah) and the main economic sectors classified by the PCBS.

Universiti Utara Malaysia

According to the PCBS classification, SMEs in Palestine are distributed across the following main sectors: Manufacturing Industry, Construction, Trade, and Services, as shown in Table 3.1.

This stratification ensured that all geographical areas and economic sectors were proportionally represented in the sample, enhancing the generalizability of the results across SMEs in the Gaza Strip. Within each stratum, SMEs were randomly selected from official lists obtained from the Ministry of National Economy, as shown in Table 3.1.

Table 3.1
Summary Results of Establishments Census 2012, 2017

Indicator	Year	
	2012	2017
West Bank		
Manufacturing Industry	13,669	15,714
Construction	429	591
Trade	49,642	54,618
Services	34,651	37,565
Total	**98,391**	**108,488**
Gaza Strip		
Manufacturing Industry	5,356	5,049
Construction	203	287
Trade	24,437	26,642
Services	16,582	18,124
Total	**46,578**	**50,102**
Total in Palestine (West Bank & Gaza Strip)	**144,969**	**158,590**

Source: (PCBS (2022). Population, Housing and Establishments Census 2017)

3.4.4.2 Sample Size

According to the PCBS, which conducted a survey in 2017 released in 2018, Palestine's operating establishments are distributed across different sectors and regions, namely the West Bank and the Gaza Strip. The data highlights the total number of establishments and their percentage distribution across four main sectors: Industry, Construction, Trade, and Services, as shown in Table 3.2. The industry sector has a total of 20,763 establishments, with 15,714 in the West Bank and 5,049 in the Gaza Strip, making up 13% of the total establishments. The construction sector includes 878 establishments, with 591 in the West Bank and 287 in the Gaza Strip, accounting for 1% of the total. Trade is the largest sector, with 81,260 establishments, 54,618 in the West Bank and 26,642 in the Gaza Strip, representing 51% of all establishments. The services sector has 55,689 establishments, with 37,565 in the West Bank and 18,124 in the Gaza Strip, comprising 35% of the total. The total number of operating establishments in Palestine is 158,590, with 108,488 in the West Bank and 50,102 in the Gaza Strip. The researcher will conduct the study on the Gaza Strip and across all SME sectors. Given that Palestine is occupied and divided into two parts, the West

Bank and Gaza Strip, with restricted movement between these areas and no geographic continuity, this segmentation justifies focusing the study on the Gaza Strip, as shown in Table 3.2.

Table 3.2
Distribution of Operating Establishments in Different Sectors by Region in Palestine

Sector	Region		Total	%
	West Bank	Gaza Strip		
Industry	15,714	5,049	20,763	13%
Construction	591	287	878	1%
Trade	54,618	26,642	81,260	51%
Services	37,565	18,124	55,689	35%
Total	**108,488**	**50,102**	**158,590**	**100%**

Source: (PCBS, (2022). Population, Housing and Establishments Census 2017)

Table 3.3
*Number of Operating Establishments in the Private Sector, Non-Governmental Organization Sector and Governmental Companies in Gaza Strip by Main Economic Activity and Employment Size Group, 2017**

Economic Activity	Employment Size Group						Total
	1-4	5-9	10-19	20-49	50-99	+100	
Mining and quarrying	12	8	3	0	0	0	**23**
Manufacturing	3,525	624	225	106	12	3	**4,495**
Electricity, gas, steam and air conditioning supply	26	4	0	2	0	7	**39**
Water supply; sewerage, waste management and remediation activities	126	23	3	1	0	0	**153**
Construction	139	68	39	18	5	1	**270**
Wholesale and retail trade; repair of motor vehicles and motorcycles	25,137	1,039	203	55	13	4	**26,451**
Transportation and storage	187	82	75	27	2	0	**373**
Accommodation and food service activities	1,999	250	67	27	6	0	**2,349**
Information and communication	203	78	36	21	8	4	**350**
Financial and insurance activities	299	49	38	18	1	1	**406**
Real estate activities	101	10	4	2	0	0	**117**
Professional, scientific and technical activities	1,086	144	32	9	0	0	**1,271**
Administrative and support service activities	601	44	4	2	1	0	**652**
Public administration and defence; compulsory social security	4	3	2	0	0	0	**9**

Universiti Utara Malaysia

Education	951	591	158	71	11	7	**1,789**
Human health and social work activities	1,278	151	83	57	15	10	**1,594**
Arts, entertainment and recreation	762	93	26	6	0	0	**887**
Other service activities	5,195	227	110	43	4	0	**5,579**
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0	0	0	0	0	0	0
Activities of extraterritorial organisations and bodies	6	1	2	0	2	2	**13**
Not stated	4	1	0	0	0	0	**5**
Total	**41,641**	**3,490**	**1,110**	**465**	**80**	**39**	**46,825**

* Does not include Auxil. Activity Establishments
Source: (PCBS, (2022). Population, Housing and Establishments Census 2017)

Table 3.4
Number and Percentage of SMEs in Gaza Stripe by Employment Size Groups and Economic Activities, 2017

Economic Activity	Employment Size Group			Total	%
	1-4	5-9	10-19		
Wholesale and retail trade; repair of motor vehicles and motorcycles	25,137	1,039	203	26379	57.05%
Other service activities	5,195	227	110	5532	11.96%
Manufacturing	3,525	624	225	4374	9.46%
Accommodation and food service activities	1,999	250	67	2316	5.01%
Education	951	591	158	1700	3.68%
Human health and social work activities	1,278	151	83	1512	3.27%
Professional, scientific and technical activities	1,086	144	32	1262	2.73%
Arts, entertainment and recreation	762	93	26	881	1.91%
Administrative and support service activities	601	44	4	649	1.40%
Financial and insurance activities	299	49	38	386	0.83%
Transportation and storage	187	82	75	344	0.74%
Information and communication	203	78	36	317	0.69%
Construction	139	68	39	246	0.53%
Water supply; sewerage, waste management and remediation activities	126	23	3	152	0.33%
Real estate activities	101	10	4	115	0.25%
Electricity, gas, steam and air conditioning supply	26	4	0	30	0.06%
Mining and quarrying	12	8	3	23	0.05%

Universiti Utara Malaysia

Public administration and defence; compulsory social security	4	3	2	9	0.02%
Activities of extraterritorial organisations and bodies	6	1	2	9	0.02%
Not stated	4	1	0	5	0.01%
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0	0	0	0	0.00%
Total	**41,641**	**3,490**	**1,110**	**46,241**	**100.00%**

Krejcie and Morgan (1970) provided a table to simplify the determination of sample size from a given population. According to their table, the sample size for a population of 50,000 is 381, and for a population of 1,000,000, it is 384. Based on this, the sample size for a population of 46,241 is assumed to be 381 for conducting the survey using the questionnaire protocol. However, due to the low response rate in Palestine, especially among owners and managers, the sample size was increased by 40 percent, resulting in a total of 533 respondents (Salkind, 1997). Furthermore, for multivariate analysis, the sample size should be at least 10 times the number of predictor variables. In this study, there are 11 predictors, so the required sample size should be 110 or more.

3.4.4.3 Data Collection and Procedure

Survey research is systematically gathering specific information about particular individuals or entities (Sekaran, 2003). Surveys are a quick, relatively inexpensive, and accurate method to investigate research phenomena (Zikmund, 2000), especially when a large number of responses is required (Creswell, 2003). Surveys can be administered in various ways, including by telephone, face-to-face, mail, and electronically (Domegan & Fleming, 2007). The data collection period will span four months, from April 2021 to the end of August 2021. The target respondents, or unit of

analysis, are owner-managers of small and medium enterprises (SMEs) across all SME sectors in Palestine.

The researcher employs multiple approaches for data collection: an online survey method using a URL link to the survey questionnaire and distributing the questionnaire face-to-face and by hand. The benefits of online research and surveys are numerous, including lower cost, faster fieldwork, increased accuracy, and high-quality responses. These methods eliminate interviewer bias and allow respondents to answer at their convenience without feeling pressured.

In addition to online methods, the researcher distributes the questionnaire directly to companies in the five governorates. The names and addresses of these companies will be obtained from the Ministry of National Economy, where businesses are registered upon establishment. This combination of distribution methods ensures comprehensive coverage and higher response rates. Furthermore, it acknowledges that some respondents prefer paper questionnaires over electronic ones, catering to their preferences and potentially increasing the overall response rate.

Universiti Utara Malaysia

3.5 Measurement and Operationalization of Variables

An operational definition outlines how a researcher plans to define and measure all the variables in a study, tailored specifically to that research (Creswell, 2012). The measurement of variables, as adapted or adopted from previous studies, is discussed as follows:

3.5.1 Measurement of Relative Advantage

Relative Advantage (RADV) is one of the core attributes of innovations described

within the DOI theory. It refers to the degree to which an innovation is perceived as offering greater benefits than the idea or practice it replaces (Rogers, 2003). In the context of technology adoption, RADV represents the perceived improvements in performance, efficiency, productivity, and competitiveness that organisations expect to achieve when adopting new technology (Chen et al., 2015; Ghobakhloo et al., 2011). Prior research has consistently shown that RADVs are among the strongest predictors of BDA across different organisational settings (Maroufkhani et al., 2020a; Verma & Chaurasia, 2019).

From the perspective of SMEs, RADV reflects the firm's belief that adopting BD will lead to meaningful improvements in decision-making, cost reduction, customer satisfaction, and market expansion. SMEs generally operate under resource constraints; therefore, they tend to adopt innovations only when the expected benefits clearly outweigh the risks or costs of investment. This aligns with findings from Premkumar and Roberts (1999), who demonstrated that innovations offering visible, tangible, and immediate benefits are more likely to be adopted in small firms.

In the present study, RADV is operationalized as the degree to which managers in SMEs perceive BD technologies as superior to current methods and capable of improving organisational performance. This includes perceptions related to efficiency gains, cost savings, improved service delivery, and increased ability to identify new opportunities. Respondents evaluated this construct using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

The measurement items for RADV in this study were adapted from validated scales used in prior research on BD and technological innovation, particularly Maroufkhani

et al. (2020), Chen et al. (2015), Ghobakhloo et al. (2011), and Premkumar and Roberts (1999). These sources have been widely used in TOE-based and DOI-based models and are considered reliable for measuring technological attributes in SMEs, as shown in Table 3.5.

Table 3.5
Measurement of Relative Advantage

#	Items	Item adapted from
1.	Big Data improves the quality of work	(Maroufkhani et al., 2020a; Chen et al., 2015; Ghobakhloo et al., 2011; Premkumar & Roberts, 1999)
2.	Big Data makes work more efficient	
3.	Big Data lowers costs	
4.	Big Data improves customer service	
5.	Big Data attracts new sales to new customers or new markets	
6.	Big Data adoption identifies new product/service opportunities	

3.5.2 Measurement of Compatibility

Compatibility (COMP) is a key attribute of innovation within the DOI theory and represents the degree to which an innovation is perceived as consistent with an organisation's existing values, operational practices, technological infrastructure, and accumulated experience (Rogers, 2003). In technology adoption studies, COMP reflects how well a new technology fits with a firm's current systems, workflows, and strategic orientation (Oliveira & Martins, 2010). A higher level of COMP indicates that adopting the technology will require fewer adjustments, less disruption, and lower implementation resistance. Prior research consistently reports that COMP is a strong and positive driver of technology acceptance across SMEs (Wang et al., 2010; Low et al., 2011; Verma & Chaurasia, 2019).

In the context of BDA, COMP relates to the extent to which BD technologies can be integrated with existing databases, analytical tools, and digital infrastructures within the firm. SMEs often struggle with limited IT capacity, fragmented data systems, and

legacy technologies. Therefore, the perceived alignment between BD solutions and existing IT configurations becomes critical for determining adoption decisions.

In this study, COMP is operationalized as the degree to which SME respondents perceive that BD technologies are consistent with their firms' existing systems, data architectures, operational processes, and technical requirements. Respondents rated their level of agreement with each item using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

All items measuring COMP were adopted from prior validated instruments commonly used in TOE and DOI studies, including Oliveira and Martins (2010), Wang et al. (2010), Low et al. (2011), and Verma and Chaurasia (2019). These studies provide reliable, widely recognized measures for assessing COMP within organisational technology adoption, as shown in Table 3.6.

Universiti Utara Malaysia

Table 3.6
Measurement of Compatibility

#	Items	Item adapted from
1.	Big Data provides flexible architecture, which is compatible to various analytical tasks.	(Oliveira & Martins, 2010; Wang et al., 2010; Low et al., 2011; Verma & Chaurasia, 2019)
2.	Big Data architecture are compatible to schemas used for storing data.	
3.	Big Data is compatible with existing technological architecture.	
4.	It is easy to synchronize external data with organisation's internal data.	

3.5.3 Measurement of Complexity

Complexity (CMPLX) is another core innovation attribute within DOI theory and refers to the degree to which a technological innovation is perceived as difficult to understand, implement, or use (Rogers, 2003). In technology adoption research, CMPLX typically reflects challenges related to system configuration, data integration,

analytical processing, and user interaction. Higher perceived CMPLX often discourages adoption, particularly in SMEs that face limited technical skills, constrained IT infrastructure, and insufficient analytical expertise (Wang et al., 2010; Ramdani et al., 2013).

In the context of big data, CMPLX arises due to the nature of unstructured and heterogeneous datasets, the need for advanced analytical tools, and the difficulty of integrating data across multiple systems and stakeholders. SMEs often lack specialized personnel capable of managing sophisticated BD architectures, increasing the perceived difficulty of adoption (Verma & Chaurasia, 2019). These barriers make CMPLX a critical technological determinant in the TOE and DOI frameworks.

In this study, CMPLX is defined as the extent to which SME managers perceive big data technologies as difficult to understand, interpret, and integrate into existing organisational systems. The construct captures challenges related to data processing, system compatibility, analytical interpretation, and overall implementation effort. Respondents rated their agreement using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

Universiti Utara Malaysia

All items measuring CMPLX were adapted from established scales used in prior studies by Wang et al. (2010), Ramdani et al. (2013), and Verma and Chaurasia (2019). These sources offer validated measurement indicators frequently applied in studies examining technological barriers in innovation adoption, as shown in Table 3.7.

Table 3.7
Measurement of Complexity

#	Items	Item adapted from
1.	It is difficult to normalize huge amount of unstructured data from multiple sources to make it compatible with structured data.	(Wang et al., 2010; Ramdani et al., 2013;

2.	The interpretation of big data analysis results to extract actionable knowledge is difficult.	Verma & Chaurasia, 2019)
3.	It is difficult to integrate data, across multiple incompatible databases among various stakeholders	
4.	It is difficult to integrate data across silos.	

3.5.4 Measurement of Trialability

Trialability (TR) is a central innovation attribute in the DOI theory and refers to the degree to which an innovation can be experimented with before full adoption (Rogers, 2003). Technologies that offer opportunities for limited experimentation enable organisations to assess their usefulness, reduce uncertainty, and better understand operational implications. Prior research demonstrates that higher TR increases the likelihood of technology adoption, particularly among SMEs, because it lowers perceived risks and allows firms to explore functionalities without major financial or operational commitments (Maroufkhani et al., 2020b).

In the context of BD analytics, TR represents the extent to which SMEs can test analytics platforms, explore their features, and evaluate their capabilities before making irreversible investment decisions. Access to free trials or pilot implementations helps smaller firms overcome uncertainties related to cost, integration, and performance, which are common barriers in resource-constrained environments.

In this study, TR is defined as the degree to which SMEs perceive that they can experiment with BD solutions prior to adoption. This includes opportunities for hands-on testing, trial access, pilot usage, ease of exiting the trial process, and low initial commitment. A five-point Likert scale (1 = strongly disagree, 5 = strongly agree) was used to assess respondents' perceptions.

Universiti Utara Malaysia

All items measuring TR were adapted from Maroufkhani et al. (2020), who developed validated scales to assess the influence of trial-based experiences on BDA in SMEs, as shown in Table 3.8.

Table 3.8
Measurement of Trialability

#	Items	Item adapted from
1.	Our company could access to a free trial before making a decision to adopt Big Data Analytics	(Maroufkhani et al., 2020b)
2.	Our company has the opportunity to try a number of Big Data Analytics applications before making a decision and try out Big Data Analytics software packages on a s sufficiently large scale	
3.	Our company is allowed to use Big Data Analytics on a trial basis long enough to see its true capabilities	
4.	It is easy to get out after testing a Big Data Analytics package	
5.	The start-up cost for using Big Data Analytics is low	

3.5.5 Measurement of Observability

Observability (OB), as defined in the DOI theory, refers to the degree to which the results, benefits, or outcomes of an innovation are visible to others (Rogers, 2003). When organisations can observe clear evidence of improved performance or successful implementation by peers, confidence in the innovation increases, reducing uncertainty and enhancing the likelihood of adoption. OB is especially relevant in SMEs, where decision-makers often rely on visible success stories and industry examples to justify investments in new technologies (Maroufkhani et al., 2020b).

In the context of BD analytics, OB reflects the extent to which SMEs can see tangible improvements achieved by competitors or business partners, such as enhanced operational efficiency, improved communication, or more effective market insights. When the benefits of big data are visible across the industry, firms become more motivated to adopt similar technologies to remain competitive and connected within their business networks.

Universiti Utara Malaysia

In this study, OB is operationalized as the degree to which SME decision-makers perceive the outcomes of big data adoption to be observable within and outside their organisation. This includes visibility of use by competitors, accessibility of BD tools internally, and clear evidence of improved performance. Responses were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

All items measuring OB were adapted from Maroufkhani et al. (2020), whose measurement scale has been widely used in BDA studies across SMEs, as shown in Table 3.9.

Table 3.9
Measurement of Observability

#	Items	Item adapted from
1.	Many competitors or business partners in the market have started using Big Data.	(Maroufkhani et al., 2020b)
2.	Using Big Data helps our company to connect with both domestic and international business partners.	
3.	There are many computers that people in the company can access to use Big Data.	
4.	Big Data shows improved results over doing business by traditional way.	

Universiti Utara Malaysia

3.5.6 Measurement of Top Management Support

Top management support (TMS) is a critical organisational factor in the TOE framework and plays a decisive role in shaping technology adoption within firms. It refers to the degree to which senior leaders demonstrate commitment, provide strategic direction, and allocate necessary resources to support the adoption of new technologies (Chen et al., 2015; Lai et al., 2018). In SMEs, where managerial decision-making is often centralized, TMS becomes even more essential, as it directly influences OR, prioritisation of innovation, and allocation of financial or technical resources (Priyadarshinee et al., 2017).

Prior studies emphasize that when top managers actively support digital transformation initiatives, organisations are more likely to overcome internal resistance, invest in new capabilities, and align technology projects with long-term strategic objectives (Maroufkhani et al., 2020a). This support often manifests in providing financial resources, encouraging training programs, championing the use of big data, and fostering a culture that embraces technological innovation.

In this research, TMS is operationalized as the degree to which SME executives and owners demonstrate commitment to the adoption of big data technologies. This includes providing adequate resources, encouraging the use of big data, expressing enthusiasm for digital transformation, and facilitating conditions that enable successful implementation. Respondents rated the items using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

All items measuring TMS were adapted from validated and widely used scales in prior studies, including Chen et al. (2015); Lai et al. (2018); Priyadarshinee et al. (2017); and Maroufkhani et al. (2020), as shown in Table 3.10.

Universiti Utara Malaysia

Table 3.10
Measurement of Top Management Support

#	Items	Item adapted from
1.	Top management would provide resources necessary for the adoption of big data.	(Chen et al., 2015; Lai et al., 2018; Priyadarshinee et al., 2017; Maroufkhani et al., 2020a)
2.	Top management would provide necessary support for the adoption of big data.	
3.	Top management would support the use of big data.	
4.	Top managers would be enthusiastic about adopting big data.	

3.5.7 Measurement of Organisational Readiness

Organisational readiness (OR) represents a key organisational factor within the TOE framework and reflects the extent to which a firm possesses the necessary financial,

technological, and human resources required to adopt and implement new technologies (Chen et al., 2015). Readiness plays a fundamental role in shaping technology adoption decisions, particularly in SMEs where resources are often scarce and managerial capabilities are limited (Maroufkhani et al., 2020a). Firms that lack adequate IT infrastructure, skilled personnel, or financial capacity are less likely to embark on technologies that require substantial investment or advanced analytical skills, such as BD analytics.

Previous studies have repeatedly shown that organisations with higher levels of readiness are better positioned to exploit technological opportunities and integrate innovations smoothly into their operations (Ramdani et al., 2013; Ghobakhloo, 2011). In the context of BD, OR includes the availability of proper data storage systems, analytical tools, financial resources, and trained staff capable of handling complex datasets. When readiness is low, organisations may experience delays, inefficiencies, or complete failure in integrating BD technologies.

Universiti Utara Malaysia

In this study, OR is defined as the extent to which SME managers believe that their firm's financial resources, IT infrastructure, analytical skills, and skilled workforce are adequate to support big data adoption. The construct was assessed using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

All items measuring OR were adapted from Chen et al. (2015) and Maroufkhani et al. (2020), whose scales have been widely applied in big data and technology adoption research, as shown in Table 3.11.

Table 3.11
Measurement of Organisational Readiness

#	Items	Item adapted from

1.	lacking capital/financial resources has prevented our company from fully exploit Big Data.	(Chen et al., 2015; Maroufkhani et al., 2020a)
2.	lacking IT infrastructure has prevented our company from exploiting Big Data.	
3.	lacking analytics capability prevent the business fully exploit Big Data.	
4.	Lacking skilled resources prevent the business fully exploit Big Data.	

3.5.8 Measurement of Competitive Pressure

Competitive pressure (COPMR) is an important environmental factor within the TOE framework. It refers to the extent to which external market forces particularly competitors motivate or compel a firm to adopt technological innovations. In dynamic and competitive environments, SMEs often face pressure to match or exceed competitors' technological capabilities to maintain market relevance and avoid losing customers (Lai et al., 2018). Prior studies indicate that when competitors adopt advanced technologies such as BD analytics, other firms may feel compelled to follow in order to remain competitive and sustain operational efficiency (Maroufkhani et al., 2020a).

Universiti Utara Malaysia

For SMEs, COPMR can be a powerful external driver of innovation adoption. Firms operating in markets where rivals increasingly rely on data-driven insights may perceive BD technologies as essential rather than optional. As competition intensifies, SMEs may view adoption as necessary to improve decision-making, enhance customer engagement, and identify new business opportunities.

In this study, COPMR is operationalized as the degree to which SME managers perceive that competition within their industry influences their decision to adopt BD analytics. Respondents indicated their agreement with each statement on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

All items measuring COPMR were adapted from Lai et al. (2018) and Maroufkhani et al. (2020), both of which provide validated measures commonly used in studies on innovation adoption within competitive environments, as shown in Table 3.12.

Table 3.12
Measurement of Competitive Pressure

#	Items	Item adapted from
1.	Our choice to adopt Big Data Analytics would be strongly influenced by what competitors in the industry are doing	(Lai et al., 2018; Maroufkhani et al., 2020a)
2.	Our firm is under pressure from competitors to adopt Big Data Analytics	
3.	Our firm would adopt Big Data Analytics in response to what competitors are doing	

3.5.9 Measurement of External Support from Vendors

External support from vendors (EXSUPP) represents a crucial environmental factor within the TOE framework. It refers to the extent to which technology vendors, consultants, or community agencies provide assistance that facilitates the adoption of new innovations such as BD analytics. This support may include training, technical guidance, troubleshooting, system customization, and continuous after-adoption support (Premkumar & Roberts, 1999; Ghobakhloo et al., 2011).

For SMEs, which often lack specialized IT knowledge and internal capabilities, EXSUPP plays a particularly vital role in reducing uncertainty and easing the adoption process. Effective vendor involvement can shorten implementation time, enhance user confidence, and improve the perceived feasibility and benefits of using BD technologies (Maduku et al., 2016). Prior research shows that SMEs with greater access to vendor training and technical assistance are more likely to adopt and sustain the use of advanced digital technologies (Maroufkhani et al., 2020b).

In this study, EXSUPP is defined as the degree to which SMEs perceive that vendors

and community agencies provide the necessary training, technical assistance, and promotional guidance to support BDA. The construct was measured using a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

All items measuring EXSUPP were adapted from Maduku et al. (2016), Premkumar and Roberts (1999), Ghobakhloo et al. (2011) and Maroufkhani et al. (2020b), as shown in Table 3.13.

Table 3.13
Measurement of External Support from Vendors

#	Items	Item adapted from
1.	Community agencies/vendors can provide required training for Big Data adoption.	(Maduku et al., 2016; Premkumar & Roberts, 1999; Ghobakhloo et al., 2011; Maroufkhani et al., 2020b)
2.	Community agencies/vendors can provide effective technical support for Big Data adoption.	
3.	Vendors actively market Big Data adoption.	

3.5.10 Measurement of Governmental Support

Governmental Support (GOVS) is a fundamental environmental factor within the TOE framework and plays an essential role in enabling and accelerating the adoption of technological innovations. It refers to the degree to which government policies, regulations, incentives, and institutional programmes encourage firms to adopt new technologies, including BD analytics (Agrawal, 2015; Gupta & Barua, 2016). In many developing and emerging economies, government intervention significantly influences firms’ digital transformation by providing financial assistance, technical training, infrastructure development, and regulatory frameworks that reduce adoption risks (Lai et al., 2018).

In the context of SMEs, GOVS is particularly critical because these firms often face resource constraints, lack of IT expertise, and concerns related to data security and

privacy. Supportive policies such as innovation grants, tax incentives, subsidised training programmes, and legal protections can reduce adoption barriers and create a favourable environment for technology investment (Maroufkhani et al., 2020a). When SMEs perceive that government initiatives address their operational challenges and enhance technological confidence, their willingness to adopt big data increases significantly.

In this study, GOVS is operationalized as the extent to which SMEs believe that government policies, incentives, and regulations facilitate and encourage the adoption of BD analytics. This includes policy encouragement, financial and technical incentives, and legal frameworks addressing security and privacy concerns. Items were measured using a five-point Likert scale from 1 ("strongly disagree") to 5 ("strongly agree").

All items measuring GOVS were adapted from Agrawal (2015), Gupta and Barua (2016), Lai et al. (2018) and Maroufkhani et al. (2020), as shown in Table 3.14.

Universiti Utara Malaysia

Table 3.14
Measurement of Governmental Support

#	Items	Item adapted from
1.	The governmental policies encourage us to adopt new information technology (e.g., big data).	(Agrawal, 2015; Gupta & Barua, 2016; Lai et al., 2018; Maroufkhani et al., 2020a)
2.	The government provides incentives for using big data analytics in government procurements and contracts such as offering technical support, training, and funding for big data.	
3.	There are some business laws to deal with the security and privacy concerns over the Big Data technology	

3.5.11 Measurement of Organisational Innovativeness

Organisational innovativeness (INNOV) is an essential internal capability that reflects an organisation's openness to new ideas, willingness to experiment, and ability to adopt novel technologies, processes, and practices (Damanpour & Schneider, 2006).

Within the DOI theory, innovativeness is considered a central determinant influencing how early or late an organisation adopts new technologies. Highly innovative firms tend to be proactive, forward-looking, and more inclined to perceive the potential benefits of innovations, including BD analytics (Shafique et al., 2019).

For SMEs, INNOV is particularly important because it reflects managerial attitudes, cultural support for change, and readiness to engage in digital transformation. Firms exhibiting strong innovativeness are more likely to explore new technologies, reconfigure processes, and invest in building technological capabilities. Recent studies demonstrate that innovativeness enhances the adoption of various digital tools, including cloud computing, artificial intelligence, blockchain technologies, and BD analytics (Le et al., 2020). Thus, INNOV acts as a strategic enabler that shapes how SMEs interpret and respond to technological opportunities and challenges.

In this research, INNOV is defined as the extent to which SME decision-makers perceive their firms as open to experimentation, supportive of creativity, and proactive in implementing new ideas and technologies. It reflects both cultural and behavioural dimensions of innovation. Respondents rated each item using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

All items measuring INNOV were adapted from Shafique et al. (2019) and Le et al. (2020), whose measurement scales are widely used in organisational innovation and technology adoption studies, as shown in Table 3.15.

Table 3.15
Measurement of Organisational Innovativeness

#	Items	Item adapted from
1.	Our company frequently tries out new ideas.	(Shafique et al., 2019; Le et al., 2020)
2.	Our company seeks out new ways to do things.	

3.	Our company is creative in its methods of operation.
4.	Our company is often the first to market with new products and services.
5.	Innovation in our company is seen as a valuable opportunity and is actively supported.
6.	Our new product introduction has increased over the last 5 years.

3.5.12 Measurement of Intention to Adopt Big Data

Intention to adopt big data (IABD) represents the dependent variable in this study and is grounded in established technology adoption theories, including the DOI theory and broader innovation-behaviour models. Intention reflects the organisation's readiness, willingness, and commitment to implementing a new technology, and it is widely recognized as the strongest predictor of actual adoption behaviour (Maduku et al., 2016). In the context of SMEs, IABD reflects management's belief that implementing BD analytics will improve business performance, enhance decision-making, and provide competitive advantage.

Universiti Utara Malaysia

Previous studies emphasize that intention captures both motivational and behavioural components indicating not only the desire to adopt but also the likelihood of taking concrete steps toward implementation (Yadegaridehkordi et al., 2018). For SMEs, intention is crucial because resource limitations often require careful planning and strong managerial commitment before adopting advanced technologies such as big data analytics (Yadegaridehkordi et al., 2020). Thus, measuring this construct provides important insight into the extent to which SMEs are prepared to transition into data-driven operations.

In this study, IABD is defined as the extent to which SME managers indicate their firm's readiness, willingness, and planned commitment to adopting and regularly using big data technologies. Respondents evaluated this construct on a five-point

Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

All items measuring intention to adopt big data were adapted from Maduku et al. (2016), Yadegaridehkordi et al. (2018), and Yadegaridehkordi et al. (2020), as shown in Table 3.16.

Table 3.16
Measurement of Intention to Adopt Big Data

#	Items	Item adapted from
1.	Our firm intends to adopt big data.	(Maduku et al., 2016; Yadegaridehkordi et al., 2020)
2.	Our firm intends to start using big data regularly in the future.	
3.	Our firm would highly recommend big data for other enterprises to adopt.	
4.	Our firm intend to use big data in the next few months.	

3.6 Questionnaire Design

This section outlines the methodology employed to measure the variables under study. In addition to general information about the organisation, the questionnaire is divided into six parts (Appendix D). The first part includes a cover letter explaining the purpose and objectives of the study. The endogenous (dependent) variable assesses the IABD among SMEs, while the exogenous (independent) variables encompass technological factors, organisational factors, and environmental factors. INNOV serves as the moderating variable.

In the questionnaire, respondents are instructed to carefully indicate their responses by checking the box corresponding to their answer for each question. Each question is preceded by a five-point Likert scale box. The Likert scale ranges from one to five, representing varying degrees of agreement with the statement (Hair et al. 2010). Likert scales are commonly utilized to measure latent variables, particularly in social science research. Respondents are asked to indicate their level of agreement or disagreement with statements pertaining to the procedures currently implemented within their

organisation. The five-point Likert scale (1 to 5) is used to measure all variables, including technological factors, organisational factors, environmental factors, and the IABD among SMEs, ranging from "strongly agree" to "strongly disagree." The Likert scale has been widely used in previous studies on BD analytics and information management (Gangwar et al., 2018; Wang et al., 2010).

3.6.1.1 Questionnaire Translation

The survey items were initially created in English. However, since the target population's primary language is Arabic, the questionnaire was translated into Arabic to facilitate better understanding among respondents. Utilizing Arabic for the research questionnaire allows the researcher to gather more insightful information by employing the native language of the target population during the data collection process. This approach also enables more effective communication with companies in Palestine.

Universiti Utara Malaysia

To ensure content validity, survey items were adapted from previous studies. A back-to-back translation procedure was employed to translate the questionnaires, allowing for a comparison between the translated version and the original version (Brislin, 1970). Initially, a native Arabic speaker fluent in both languages and an expert in the AIS area translated the original items into Arabic. An Arabic language expert then verified the Arabic version of the questionnaire. Subsequently, another expert fluent in both languages translated the verified Arabic version back into English. Finally, the outputs were compared with the original version to validate the accuracy of the content.

3.7 Data Analysis Techniques

Data were collected via questionnaires distributed to respondents both online using Google Forms and face-to-face to enhance response rates. Data analysis were conducted using statistical analysis software SPSS 26 and PLS-SEM 3.2.7. The analytical techniques employed in this study include descriptive statistics, frequency analysis, percentage calculations, mean, standard deviations, factor analysis, simple regression model, and Structural Equation Modelling (SEM). The data received from respondents will be coded into the Statistical Package for the Social Sciences (SPSS). Initially, a preliminary analysis will be conducted to ensure the data accurately represents the situation under investigation in this study. Subsequently, the data will be transferred into SEM-PLS and analysed using a two-step approach: measurement model assessment to test for reliability and validity, followed by structural model assessment to examine the direct and indirect effects, thereby addressing the study's objectives.

Universiti Utara Malaysia

Structural Equation Modelling is a second-generation multivariate data analysis technique that addresses the limitations of earlier, first-generation methods. According to Hair et al. (2016), SEM is considered more powerful for testing multiple relationships among several variables simultaneously. It can evaluate the relationships between constructs presented by a series of statistical equations, as opposed to using multiple regression equations independently. SEM is widely used in research due to its ability to assess both linear and additive causal relationships within a model (Hair et al., 2016). This is because SEM integrates the capabilities of factor analysis and multiple regression into a single, comprehensive framework.

Hair, Sarstedt, Ringle, Smith, and Reams (2014) identified two types of SEM:

covariance-based SEM (CB-SEM) and variance-based SEM (VB-SEM). CB-SEM focuses on reproducing the theoretical covariance matrix, emphasizing the confirmation or disconfirmation of the theoretical model relationships rather than the explained variance. In contrast, VB-SEM, also known as PLS-SEM, aims to maximize the explained variance or predict an endogenous latent variable. Therefore, PLS-SEM is particularly suitable for research that emphasizes theory prediction and explanatory research by elaborating on the variance observed in the dependent constructs or variables.

Although both CB-SEM and PLS-SEM originate from the same foundational concepts, CB-SEM has traditionally garnered more attention in previous studies (Hair et al., 2012). However, PLS-SEM has seen exponential growth in recent years and is anticipated to become widely adopted as a more powerful statistical analysis tool due to its unique features and advancements in its methodology (Hair et al., 2012; Henseler et al., 2015). Hair et al. (2011) also noted that PLS-SEM, both theoretically and practically, performs similar functions to multiple regression. It evaluates data quality and explains the variance in endogenous constructs by utilizing both measurement and structural models.

Given that the present study is predictive rather than confirmatory of an existing theory, PLS-SEM was chosen as the appropriate tool for data analysis. This choice aligns with the guidelines established in the literature (Hair et al., 2011). One of the primary advantages of adopting PLS-SEM is its robustness in handling data regardless of its normality distribution. Although the normality tests indicated that the data distribution is reasonably normal, PLS-SEM remains a powerful tool due to its ability to effectively handle measurement errors and its greater statistical power for testing or

confirming theories compared to CB-SEM (Henseler et al., 2015; Henseler et al., 2009). Additionally, PLS-SEM is particularly suitable for predictive and explanatory research, making it the 'silver bullet' for estimating causal models when used correctly (Hair et al., 2011).

3.8 Chapter Summary

This chapter outlines the research framework and defines the main research variables. Based on this framework, eleven research hypotheses are proposed for further investigation. The chapter also explains the research design and methods used to answer the research questions, with measurement items adapted from previous studies. It describes the population setting, sampling procedures, and reasons for selecting Palestinian SME managers as the focus of analysis. Finally, the chapter details the data collection procedures and statistical techniques used in this study. The next chapter presents the analysis results.

Universiti Utara Malaysia

CHAPTER 4

RESULT OF STUDY

4.1 Introduction

This chapter deliberates the finding from the data analysis which comprises preliminary analysis, empirical results of measurement model and testing structural model of the study. Discussion on the preliminary analysis includes data screening, common method bias and the profile of the respondents. This was followed by analysis of measurement model which covers the reliability and validity of the model. The discussion of structural model includes collinearity assessment, the path coefficient of the structural model, the coefficient of determination, effect size, and predictive relevance. Next, the discussion of hypothesis testing and moderating effect is presented.

Universiti Utara Malaysia

4.2 Data Screening

To obtain the desired response, 533 questionnaires were distributed during three months data collection period. A total 308 questionnaires were completed, giving the response rate of 57.78 percent. Out of 308 questionnaires received, 36 questionnaires were excluded because the respondent did not fulfil the requirement.

The remaining 272 cases were analysed with SPSS 26.0 and subjected to a number of standard procedures such as examining for missing values, outliers, and data distribution. For missing values, the author decided to deal with the issue by using the mean value replacement procedure of SPSS 26.0. The reason for choosing this procedure was because the problem of missing values in the data set was minimal.

Therefore, mean values procedures were done only for the missing data for items associated with the constructs, as shown in Table 4.1.

Table 4.1
Summary on the Rate of Return Questionnaires

	Total/Percentage
Distributed	533
Returned questionnaire	308
Response rate	57.78%
Unusable questionnaire	36
Usable questionnaires	**272**

Before commencing the data analysis, the data were screened to check for normality distribution. This allows for examining the essential variable that used in testing the hypotheses of study.

4.2.1 Normality Test

Normality refers to the shape of the data distribution for an individual metric variable and its correspondence to the normal distribution. Therefore, if the variation of the data from the normal distribution is sufficiently large, the subsequent statistical analysis is invalid (Hair et al., 2010).

Subsequently, the skewness and kurtosis tests were performed in order to examine the normality of data distribution. The results revealed that the values for skewness ranged from .518 to -.702 and values from kurtosis ranged from .376 to -1.136. According to Kline (2005), the conventional criteria of normality for skewness ranged from -3 to 3 while for kurtosis are raged from -10 to 10. Therefore, the scores for all variables in this study were found to be reasonably distributed (see Appendix B).

Universiti Utara Malaysia

4.3 Common Method Bias

In the current study, the measurement of the construct was based on the assessment of managers and owners in SMEs in Palestine. As the data were gathered from the same survey instruments and the same level of respondents, the possibility of common method bias in data, Harmans's single factor test was conducted to determine whether a single factor counts for a majority of the variance explained (Podsakoff & Organ 1986). The results demonstrated the presence of twelve factors with eigenvalues that the first single factor accounted 37.79% of the variance which was less than threshold value of 50% (Podsakoff & Organ 1986). Therefore, the common, method bias was not viewed as a major issue on this study, as shown in Table 4.2.

Table 4.2
Common Bias

	Initial Eigenvalues		Extraction Sums of Squared Loadings		
Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
16.016	39.064	39.064	15.492	37.785	37.785

Universiti Utara Malaysia

4.4 Demographic Analysis

This section focuses on providing general information on the respondents. Using SPSS Frequencies and Descriptive Analysis, the investigation concentrates on two main components. The first part is mainly on the demographics of the firms, followed by a review of the respondents' backgrounds.

4.4.1 Companies Profile

The distribution of 272 usable responses representing the whole industry from different types of SMEs in Palestine has been listed in Table 4.3.

Table 4.3
Summary of Companies' Profile

	Frequency	Percentage
Does your company intend to adopt big data?		
Yes	272	88.31
No	36	11.69
Total	**308**	**100.00**
Our firm plans using big data in the next?		
Three months	38	13.97
Six months	55	20.22
Nine months	72	26.47
One year	62	22.79
Others	45	16.54
Total	**272**	**100.00**
Distribution of firms' location		
Gaza district	112	41.18
Khan Yunis district	52	19.12
North district	46	16.91
Middle district	32	11.76
Rafah district	30	11.03
Total	**272**	**100.00**
Distribution of SMEs According to Industries		
Manufacturing	15	5.51
Services	85	31.25
Merchandizing	122	44.85
Construction	7	2.57
Other	43	15.81
Total	**272**	**100.00**
Number of equivalent full-Time employees		
1–4	12	4.41
5–1	246	90.44
20–49	14	5.15
Above 50	0	0.00
Total	**272**	**100.00**
Company's 2021 annual sales/ turnover		
< USD 20,000	7	2.57
USD 20,001 – USD 200,000	95	34.93
USD 200,001 –500,000	157	57.72
Above USD 500,001	13	4.78
Total	**272**	**100.00**
Company's 2021 capital		
< USD 5000	8	2.94
USD 5,001 – USD 50,000	102	37.50
USD 50,001 – USD 100,000	144	52.94
Above USD 100,001	18	6.62
Total	**272**	**100.00**
Ages of Firms		
Less than 5 years	52	19.12
5 – 10 years	76	27.94
11 – 20 years	66	24.26
21 – 30 years	47	17.28

Universiti Utara Malaysia

	Frequency	Percentage
31 – 40 years	18	6.62
More than 40 years	13	4.78
Total	**272**	**100.00**

Table 4.3 provides an overview of various aspects related to the companies included in the study. It presents information on the companies' IABD, their plans for utilising BD in the future, distribution across different industries, geographic locations, ages of firms, number of equivalent full-time employees, annual sales/turnover, and capital.

Regarding the adoption of BD, 88.31% of the companies expressed their intention to adopt it, while 11.69% indicated they do not plan to adopt it. Among the companies that plan to adopt BD, the majority (26.47%) expect to do so within the next nine months.

The distribution across industries shows that the largest proportion of participating SMEs operate in the merchandising sector (44.85%), followed by services (31.25%), while manufacturing (5.51%), construction (2.57%), and other sectors (15.81%) represent smaller shares of the sample.

Geographically, SMEs are concentrated mainly in the Gaza district (41.18%), followed by Khan Yunis (19.12%), North Gaza (16.91%), Middle area (11.76%), and Rafah (11.03%). This distribution reflects the broader economic density across the Gaza Strip.

Firm age distribution indicates that the largest group of companies has been operating for 5–10 years (27.94%), followed by firms aged 11–20 years (24.26%). Younger firms (less than 5 years) represent 19.12%, while older firms (more than 30 years) form a smaller proportion of the sample.

With respect to employment size, the revised classification shows that most companies fall within the 5–19 employees category (90.44%), indicating that the majority of SMEs in the sample are medium-small in structure. Only 4.41% of firms employ 1–4 workers, while 5.15% employ between 20–49 workers, and none reported having more than 50 employees. This distribution aligns with the typical SME structure in the region, where micro and small enterprises are predominant.

Regarding annual sales/turnover in 2021, more than half of the firms (57.72%) reported revenues between USD 200,001 and USD 500,000, followed by 34.93% within the USD 20,001–200,000 range. A small percentage recorded sales below USD 20,000 (2.57%) or above USD 500,001 (4.78%).

Lastly, capital structure shows that most companies (52.94%) have capital between USD 50,001 and USD 100,000, while 37.50% fall within USD 5,001–50,000. Only a small proportion reported capital below USD 5,000 (2.94%) or above USD 100,001 (6.62%).

Universiti Utara Malaysia

Overall, the table provides a clear and representative profile of SMEs in the sample. It reflects their structural characteristics, financial capacity, geographic distribution, and readiness for BDA, offering valuable insights into the business landscape in the Palestinian SME sector.

4.4.2 Respondents' Profile

Table 4.4 provides information on the profile of the respondents participating in the study. It includes data on the positions of the respondents in their respective

companies, the length of time they have held their current positions, and their academic qualifications.

Table 4.4
Respondents' Profile

	Frequency	Percent
Length of time holding current position		
Below 5 years	32	11.76
6 to 10 years	118	43.38
11 to 20 years	106	38.97
Above 20 years	16	5.88
Total	**272**	**100.00**
Academic Level Qualification		
Diploma	32	11.76
Bachelor degree	153	56.25
Master / PhD	74	27.21
Professional qualification	5	1.84
Others	8	2.94
Total	**272**	**100.00**
Positions of respondents in companies		
Top management	138	50.74
Middle management	46	16.91
First level management	87	31.99
Total	271	99.63
Missing	1	0.37
Total	**272**	**100.00**

Universiti Utara Malaysia

Regarding the length of time holding their current positions, the largest proportion of respondents (43.38%) have been in their positions for 6 to 10 years. This is followed by 38.97% of respondents who have held their positions for 11 to 20 years. A smaller proportion of respondents have held their positions for below 5 years (11.76%) or above 20 years (5.88%).

In terms of academic qualifications, the majority of respondents (56.25%) hold a Bachelor's degree. Master's and PhD degrees are held by 27.21% of the respondents, indicating a significant level of higher education among the sample. A smaller proportion of respondents have a diploma (11.76%), professional qualifications (1.84%), or other qualifications (2.94%).

In terms of positions, the majority of respondents (50.74%) are in top management roles, indicating that they hold senior positions within their organisations. Middle management positions are represented by 16.91% of the respondents, while first-level management positions account for 31.99% of the sample. It is worth noting that there is a small discrepancy in the total frequency, with one missing response.

Overall, the table provides valuable insights into the profile of the respondents in terms of their positions within the companies, length of time in their current positions, and academic qualifications. These details help establish the expertise and experience of the individuals participating in the study, providing credibility to the research findings.

4.5 Results of Main Analyses

This section describes in greater detail the results of main analyses using PLS-SEM by applying SmartPLS 3.3.2 The results of the measurement, model, structural model, hypothesis testing, and moderating effect are presented in this section.

Universiti Utara Malaysia

4.5.1 Non-Response bias

One of the main sources of survey-based studies' errors in non-response bias (Groves et al., 2006) which could lead to important concern on the reliability and validity of the survey results (Fowler, 2009). In this study, considerable effort was made to achieve a reasonable response rate following Dillman's (2000) method. Thus, the questionnaires were emailed in three waves. To test for non-response bias, Armstrong and Overton (1977) assumed that late respondents have more characteristics of non-respondents than early respondents. Therefore, early and late respondents were compared along all items and constructs in the study (Armstrong & Overton, 1977). Early responses are defined in this study as responses received before sending the first

reminder (30 days from the first mailing), whereas late responses are those received after that date. According to this criterion, 130 responses were considered as early responses and 142 responses were considered as late responses. Hence, the sample is split into two parts, based on the date of response. Resulting in groups of early and late respondents is shown in Table 4.5. The constructs of early and late respondents are subsequently tested for significant differences by means of t test. The result of analysis, show no significant differences ($p > 0.05$) between the two samples along the constructs of study, suggesting that non-response bias is not present in the data.

Table 4.5
T-test Result for Comparing Early and Late Responses.

	date	N	Mean	SD	t	p value
RADV	Early	130	3.185	1.067	-1.483	0.620
	Late	142	3.379	1.092		
COMP	Early	130	3.281	1.012	-1.010	0.427
	Late	142	3.403	0.985		
CMPLX	Early	130	3.087	1.020	-0.486	0.449
	Late	142	3.148	1.057		
TR	Early	130	3.562	0.448	1.421	0.264
	Late	142	3.482	0.476		
OB	Early	130	3.178	1.054	-2.170	0.248
	Late	142	3.449	1.004		
TMS	Early	130	3.467	1.019	0.226	0.359
	Late	142	3.438	1.085		
OR	Early	130	3.165	0.997	-1.476	0.413
	Late	142	3.350	1.064		
COMPR	Early	130	3.310	0.992	-0.961	0.184
	Late	142	3.434	1.124		
EXSUPP	Early	130	3.395	0.873	0.141	0.866
	Late	142	3.380	0.837		
GOVS	Early	130	3.323	1.093	-0.425	0.246
	Late	142	3.378	1.035		
INNOV	Early	130	3.334	0.971	-0.979	0.401
	Late	142	3.454	1.039		
IABD	Early	130	3.413	1.076	-0.962	0.413
	Late	142	3.542	1.127		

RADV = Relative advantage; COMP = Compatibility; CMPLX = Complexity; TR = Trialability; OB = Observability; TMS = Top Management Support; OR = Organisational Readiness; COMPR = Competitive pressure; EXSUPP = External support from vendors; GOVS = Governmental Support; INNOV = Innovation of organisations; IABD = Intention to Adopt Big Data.

Universiti Utara Malaysia

4.5.2 Descriptive Statistics Results

The measurements of study variables were 51 questions selected five points Likert scale ranging from strongly disagree to strongly agree. Based on Table 4.6, the mean of each variable is higher than the median of the scale (3). The descriptive statistics include the display of central tendency and dispersion measures. These measures include the mean, median and standard deviation. According to, descriptive statistics for each item of the variables it has been shown in Appendix A.

Table 4.6
Descriptive Statistics.

Variables	Mean	Median	S.D.
Relative advantage	3.2862	3.6667	1.0827
Compatibility	3.3447	3.5000	0.9979
Complexity	3.1186	3.2500	1.0382
Trialability	3.5199	3.6000	0.4638
Observability	3.3199	3.4000	1.0351
Top Management Support	3.4522	3.6250	1.0519
Organisational Readiness	3.2619	3.3750	1.0347
Competitive pressure	3.3750	3.3333	1.0626
External support from vendors	3.3873	3.3333	0.8531
Governmental Support	3.3517	3.6667	1.0615
Innovation of organisations	3.3965	3.4286	1.0068
Intention to Adopt Big Data	3.4807	3.7500	1.1028

The correlation between variables was examined by calculating Pearson's product correlation coefficient. The scanning of the correlation matrix indicates that there are high correlations (greater than 0.50) among the predictive and the moderating variable. The result of the correlations points out that the multicollinearity assumption is unlikely to be a problem in the subsequent related analyses (Tabacknick et al., 2001). Table 4.7-4.10 displays the correlation matrix for all variables. All of the variables reveal positive and significant correlation with each other. The correlations among construct items are presented in Appendix C.

Universiti Utara Malaysia

Table 4.7
Correlation Matrix between Technological Factors.

	RADV	COMP	CMPLX	TR	OB	Technological
RADV	1	.474**	.473**	-0.008	.457**	.743**
COMP	.474**	1	.583**	0.085	.572**	.811**
CMPLX	.473**	.583**	1	0.083	.574**	.816**
TR	-0.008	0.085	0.083	1	0.063	.204**
OB	.457**	.572**	.574**	0.063	1	.804**
N	272	272	272	272	272	272

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.8
Correlation Matrix between Organisational Factors

	TMS	OR	Organisational
TMS	1	-.516**	.504**
OR	-.516**	1	.479**
N	272	272	272

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.9
Correlation Matrix between Environmental Factors

	COMPR	EXSUPP	GOVS	Environmental
COMPR	1	.120*	.545**	.812**
EXSUPP	.120*	1	0.101	.506**
GOVS	.545**	0.101	1	.804**
N	272	272	272	272

**. Correlation is significant at the 0.01 level (2-tailed).

Universiti Utara Malaysia

Table 4.10
Correlation Matrix between T-O-E Constructions

	Technological	Organisational	Environmental	T-O-E
Technological	1	.139*	.715**	.847**
Organisational	.139*	1	.258**	.532**
Environmental	.715**	.258**	1	.896**
N	272	272	272	272

**. Correlation is significant at the 0.01 level (2-tailed).

4.5.3 Analysis and Result of Measurement Model

The assessment of the measurement model involves examining the relationship between the construct and its items. For reflective measurement model, the examination includes investigating the indicator loadings, indicator reliability, internal consistent reliability, convergent validity, and discriminant validity.

With regard to indicator loadings, the common rule of thumb is that item loadings should be 0.708 or higher (Chin, 2010; Fornell & Larcker, 1981). However, Hair et al. (2013) noted that weaker item loadings are frequently observed in social science research, and removing such items must be approached with caution, as this may compromise the content validity of the constructs. Furthermore, the removal of items with outer loadings between 0.40 and 0.70 is permissible if deleting the item leads to an improvement in composite reliability and average variance extracted (AVE) (Hair et al., 2014).

The results of the PLS algorithm revealed that most indicator loadings (twelve items) exceeded 0.70 and were below 0.85. One item had a loading between 0.60 and 0.70, four items showed loadings between 0.50 and 0.60, six items had loadings below 0.50, and two items recorded loadings above 0.85.

Next, discriminant validity was assessed by examining the Fornell-Larcker criterion, cross-loading, and HTMT criterion of the construct. For this purpose, individual item reliability was further examined for its cross-loading. All items' loadings were checked to ensure that the loading is higher in its corresponding construct than others. As recommended, each item loading should exceed the cross-loading by at least 0.10 (Gorla et al., 2010).

The composite reliability and AVE of the construct were assessed after the removal of the items with loading and cross-loading issues. The result demonstrates high convergent validity with GOVS displaying the highest AVE, which is 0.899 and OR showed the lowest AVE value, which+h is 0.612, exceeding the required AVE minimum level of 0.5 (Table 4.11).

Universiti Utara Malaysia

Table 4.11
Constructs Items, Indicator's Reliability, and AVE

		Original Sample (O)		Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
		Loading	Indicator reliability			
RADV	Big Data improves the quality of work	0.896	0.896	0.953	0.962	0.809
	Big Data makes work more efficient	0.889	0.889			
	Big Data lowers costs	0.904	0.904			
	Big Data improves customer service	0.898	0.898			
	Big Data attracts new sales to new customers or new markets	0.917	0.917			
	Big Data adoption identifies new product/service opportunities	0.893	0.893			
COMP	Big Data provides flexible architecture, which is compatible to various analytical tasks.	0.932	0.933	0.921	0.95	0.864
	Big Data architecture are compatible to schemas used for storing data.	0.929	0.932			
	Big Data is compatible with existing technological architecture.	0.924	0.924			
	It is easy to synchronize external data with organisation's internal data.	-0.128	0.124			
CMPLX	It is difficult to normalize huge amount of unstructured data from multiple sources to make it compatible with structured data.	0.907	0.907	0.932	0.951	0.830
	The interpretation of big data analysis results to extract actionable knowledge is difficult.	0.904	0.904			
	It is difficult to integrate data, across multiple incompatible databases among various stakeholders	0.919	0.919			
	It is difficult to integrate data across silos.	0.914	0.914			
TR	Our company could access to a free trial before deciding to adopt Big Data Analytics	0.864	0.864	0.93	0.947	0.781
	Our company could try several Big Data Analytics applications before deciding and try out Big Data Analytics software packages on a s sufficiently large scale	0.889	0.889			
	Our company is allowed to use Big Data Analytics on a trial basis long enough to see its true capabilities	0.904	0.904			
	It is easy to get out after testing a Big Data Analytics package	0.869	0.869			
	The start-up cost for using Big Data Analytics is low	0.891	0.891			
OB	Many competitors or business partners in the market have started using Big Data.	0.918	0.918	0.935	0.953	0.837
	Using Big Data helps our company to connect with both domestic and international business partners.	0.914	0.914			
	There are many computers that people in the company can access to use Big Data.	0.907	0.907			
	Big Data shows improved results over doing business by traditional way.	0.919	0.919			
TMS	Top management would provide resources necessary for the adoption of big data.	0.904	0.904	0.932	0.952	0.831
	Top management would provide necessary support for the adoption of big data.	0.913	0.913			
	Top management would support the use of big data.	0.922	0.922			

Universiti Utara Malaysia

	Top managers would be enthusiastic about adopting big data.	0.908	0.908			
OR	lacking capital/financial resources has prevented our company from fully exploit Big Data.	0.441	0.95	0.846	0.82	0.612
	lacking IT infrastructure has prevented our company from exploiting Big Data.	0.898	0.441			
	lacking analytics capability prevent the business fully exploit Big Data.	0.726	0.771			
	Lacking skilled resources prevent the business fully exploit Big Data.	0.556	0.583			
COMPR	Our choice to adopt Big Data Analytics would be strongly influenced by what competitors in the industry are doing	0.910	0.910	0.929	0.949	0.824
	Our firm is under pressure from competitors to adopt Big Data Analytics	0.909	0.909			
	Our firm would adopt Big Data Analytics in response to what competitors are doing	0.908	0.908			
EXSUPP	Community agencies/vendors can provide required training for Big Data adoption.	0.903	0.903	0.901	0.938	0.835
	Community agencies/vendors can provide effective technical support for Big Data adoption.	0.928	0.928			
	Vendors actively market Big Data adoption.	0.911	0.911			
GOVS	The governmental policies encourage us to adopt new information technology (e.g., big data).	0.939	0.939	0.943	0.964	0.899
	The government provides incentives for using big data analytics in government procurements and contracts such as offering technical support, training, and funding for big data.	0.938	0.938			
	There are some business laws to deal with the security and privacy concerns over the Big Data technology	0.967	0.967			
INNOV	Our company frequently tries out new ideas.	0.905	0.905	0.855	0.916	0.693
	Our company seeks out new ways to do things.	-0.071	-0.071			
	Our company is creative in its methods of operation.	0.915	0.915			
	Our company is often the first to market with new products and services.	0.913	0.913			
	Innovation in our company is seen as a valuable opportunity and is actively supported.	0.901	0.901			
	Our new product introduction has increased over the last 5 years.	0.923	0.923			
IABD	Our firm intends to adopt big data.	0.916	0.916	0.855	0.916	0.693
	Our firm intends to start using big data regularly in the future.	0.896	0.896			
	Our firm would highly recommend big data for other enterprises to adopt.	0.921	0.921			
	Our firm intend to use big data in the next few months.	0.926	0.926			

Universiti Utara Malaysia

RADV = Relative advantage; COMP = Compatibility; CMPLX = Complexity; TR = Trialability; OB = Observability; TMS = Top Management Support; OR = Organisational Readiness; COMPR = Competitive pressure; EXSUPP = External support from vendors; GOVS = Governmental Support; INNOV = Innovation of organisations; IABD = Intention to Adopt Big Data.

After an assessment of item level discriminant validity was done by checking for cross-loading, as assessment of construct discriminant validity was carried out by checking Fornell-Larcker criterion. Fornell-Larcker criterion postulates that the square root of each construct's AVE should be greater than latent variables' correlation with any other constructs in the model (Fornell & Larcher, 1981). Table 4.12 illustrates that the square root of AVE for eleven reflective constructs are higher than the correlation with other constructs. Another alternative approach to assessing the discriminant validity is through HTMT criterion, HTMT approach is proposed through low sensitivity issue of cross-loading and Fronell-Larcker criterion which only works well in situations with heterogeneous loading patterns and high sample sizes (Henseler et al., 2015). The HTMT result of this study revealed that the findings satisfy the threshold criteria of HTMT 0.90 (see Table 4.13). Regarding to Hair et al. (2016) the confidence interval of the HTMT statistic should not include the value 1 for all combinations of constructs. All things considered, the finding suggests the adequate discriminant validity of the constructs and items tested for this study.

Universiti Utara Malaysia

Table 4.12
Discriminant Validity – Fornell-Larcker Criterion

	COMPR	COMP	CMPLX	EXSUPP	GOVS	IABD	OB	OR	RADV	TMS	TR
COMPR	**0.807**										
COMP	0.169	**0.908**									
CMPLX	0.179	0.583	**0.911**								
EXSUPP	0.191	0.57	0.673	**0.914**							
GOVS	0.176	0.535	0.573	0.546	**0.948**						
IABD	0.413	0.686	0.72	0.73	0.662	**0.915**					
OB	-0.229	-0.461	-0.422	-0.397	-0.397	-0.659	**0.915**				
OR	0.029	0.093	0.197	0.091	0.097	0.064	0.018	**0.678**			
RADV	0.16	0.475	0.474	0.527	0.462	0.625	-0.423	0.023	**0.900**		
TMS	0.205	0.619	0.62	0.625	0.578	0.778	-0.516	0.098	0.492	**0.912**	
TR	0.245	0.574	0.575	0.575	0.535	0.723	-0.555	0.013	0.458	0.591	**0.884**

Table 4.13
Discriminant Validity-Heterotrait-Monotrait (HTMT)

	COMPR	COMP	CMPLX	EXSUPP	GOVS	IABD	OB	OR	RADV	TMS	TR
COMPR											
COMP	0.180										
CMPLX	0.190	0.627									
EXSUPP	0.203	0.623	0.734								
GOVS	0.184	0.572	0.611	0.591							
IABD	0.442	0.735	0.770	0.795	0.705						
OB	0.244	0.493	0.451	0.432	0.422	0.704					
OR	0.037	0.075	0.259	0.137	0.113	0.043	0.069				
RADV	0.166	0.504	0.502	0.568	0.486	0.661	0.448	0.03			
TMS	0.218	0.664	0.665	0.682	0.617	0.832	0.553	0.108	0.521		
TR	0.262	0.614	0.615	0.628	0.57	0.773	0.593	0.041	0.485	0.633	

4.5.4 Assessing and Testing The Structural Model (Hypothesis)

After establishing the measurement model in terms of reliability and validity, the next step is assessing and testing structural model. Assessment of structural model involves determining how well empirical data support the theory and therefore to decide if the theory or concepts are empirically verified for the predicted hypothesis. The inspection comprised of assessing the structural model for collinearity issues, the level of R^2, the effect of sizes (f^2), path coefficient estimates, and the predictive relevance (Q^2) (Hair et al., 2013).

4.5.1.1 Collinearity Assessment

Assessing the structural model for collinearity issues can be obtained by referring to collinearity statistics, variance inflation factor (VIF) under the PLS algorithm procedure in SmartPLS 3.2. In the context of PLS-SEM, a tolerance value of 0.20 or

lower and a VIF value of 5 and higher respectively indicate a potential collinearity problem (Hair et al., 2011).

Table 4.14 is showing that the VIF output for each construct was much less than the common cut-off threshold of 5. Hence, collinearity among the predictor constructs was not an issue in the structural model proposed in this study.

Table 4.14
VIF Values among Model Predictors

Predictors	Dependent
	Intention to Adopt BD (IABD)
COMPR	2.455
COMP	2.405
CMPLX	2.812
EXSUPP	2.725
GOVS	2.289
OB	1.786
OR	1.108
RADV	1.954
TMS	2.848
TR	2.871

Universiti Utara Malaysia

4.5.1.2 Coefficient of Determination

Considering that PLS structural equation modeling is centred on prediction and its main objective is to maximize the variance of the dependent variables, the important criterion in evaluating a PLS structural equation modeling is the assessment of the coefficient of determination (R2) of the endogenous constructs (Chin, 2010).

Achieving the high R2 is preferable as it indicates higher level of predictive accuracy. In accounting literature, R^2 values if 0.75 for latent variables is considered as substantial, 0.50 as moderate, and 0.25 as weak (Hair et al., 2014). Based on the results of the R^2, the conceptual model is displaying large portion of the variance in the endogenous construct as shown in Table 4.15 because R^2 values for the intention to

adopt big data 0.909. Therefore, the explanatory power of the model proposed for this study was at satisfactory level.

Table 4.15
Results of R^2

	R square	R Square Adjusted
IABD	0.909	0.901

4.5.1.3 Blindfolding and Predictive Relevance Q2

Another important aspect of structural model evaluation is the predictive relevance model. For this purpose, the Stone-Geisser's Q2 was examined with the use of blindfolding procedures. As shown in Table 4.16 blind procedures (with omission distance of 7), yielded positive Q2 values for all endogenous constructs suggesting predictive relevance of the model (Chin, 2010; Hair et al., 2011).

Table 4.16
Results of Q^2

	SSO	SSE	Q^2 (=1-SSE/SSO)
IABD	1088.000	277.444	0.745

4.5.1.4 Effect Size

The effect size f2 is a measure used to evaluate the relevance of each predictor (exogenous) construct on an endogenous construct (Hair et al., 2013). It determines the extent of the contribution of exogenous construct to the R^2 value of a target construct in the structural model. The f^2 values of 0.02, 0.15, and 0.35 signify as having small, medium, and large degree of predictive relevance, respectively. Table 4.17 displays the result of the effect sizes for the structural model. The f^2 values of all significant predictors were found to have a larger effect on their endogenous variables compared to the insignificant predictors. The result revealed that the highest effect size

of the model is on the effect of RADV (0.145), followed by medium effect size of OR (0.109). This effect size for this model ranged from large to small effect size.

Table 4.17
Result of f2

	Intention to Adopt BD (IABD)
COMPR	0.006
COMP	0.038
CMPLX	0.032
EXSUPP	0.065
GOVS	0.071
INNOV	0.009
IABD	0.098
OB	0.014
OR	0.109
RADV	0.145
TMS	0.032

4.5.5 Hypothesis Testing

The path coefficient in the structural model was inspected by running PLS Algorithm function, estimates are obtained for the structural relationship, which represent the hypothesized relationships. The path coefficient of a SmartPLS 3.2 model has the same interpretation as standardized beta weight in a regression analysis. Estimated path coefficient range from -1 to +1 with a path coefficient close to +1 indicates strong positive relationship and -1 signifies a strong negative relationship, while a path coefficient close to 0 suggests a weak relationship. The significance of the model's structural path was further inspected by running the bootstrapping procedure in SmartPLS 3.2 with 5000 samples and 272 cases. Table 4.18 shows the significance testing result encompassing the path coefficient, the standard error, t-statistic, and the significance level of the analysis excluding the mediating effect. Meanwhile, the results will present the significance testing excluding the moderating effect of INNOV

as moderator in the relationship between T-O-E construct and the IABD in the following section.

Table 4.18
Significance Testing Results of The Structural Model Path Coefficients

Path	beta	SE	T Statistics	P Values
RADV -> IABD	0.122	0.032	3.760	0.000
COMP -> IABD	0.082	0.032	2.544	0.011
CMPLX -> IABD	0.140	0.033	4.227	0.000
TR -> IABD	0.110	0.030	3.668	0.000
OB -> IABD	-0.183	0.029	6.306	0.000
TMS -> IABD	0.226	0.034	6.688	0.000
OR -> IABD	-0.025	0.036	0.694	0.488
COMPR -> IABD	0.060	0.113	0.531	0.595
EXSUPP -> IABD	0.159	0.032	4.930	0.000
GOVS -> IABD	0.099	0.029	3.430	0.001
INNOV -> IABD	0.149	0.100	1.495	0.006

Without including the moderation effect, the hypothesis testing examined the direct paths from the TOE and DOI factors to the IABD. Based on the significance level of 5 percent, which is widely accepted in business and management research (Hair et al., 2013), the results indicate that most paths in the structural model were statistically significant. Specifically, RADV ($\beta = 0.122$, $p < 0.05$), COMP ($\beta = 0.082$, $p < 0.05$), CMPLX ($\beta = 0.140$, $p < 0.05$), TR ($\beta = 0.110$, $p < 0.05$), TMS ($\beta = 0.226$, $p < 0.05$), EXSUPP ($\beta = 0.159$, $p < 0.05$), and GOVS ($\beta = 0.099$, $p < 0.05$) all demonstrated significant positive effects on the IABD. Likewise, INNOV showed a significant direct effect ($\beta = 0.149$, $p < 0.05$).

In contrast, OB ($\beta = –0.183$, $p < 0.05$) showed a significant but negative effect, while OR ($\beta = –0.025$, $p > 0.05$) and COMPR ($\beta = 0.060$, $p > 0.05$) were found to be statistically insignificant at the 5 percent level.

Universiti Utara Malaysia

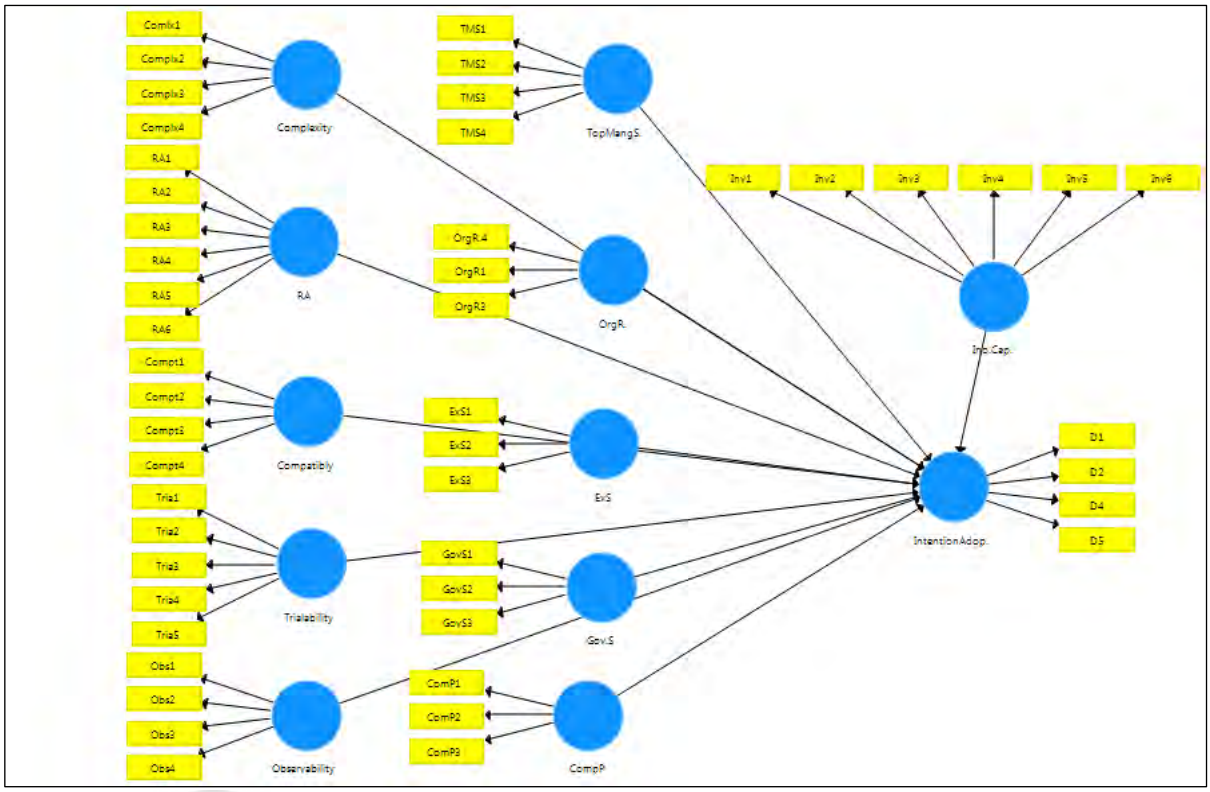


Figure 4.1
Results of the First Structural Model

Figure 4.1 approve that technological, organisational, and environmental are significantly influence on IABD.

Universiti Utara Malaysia

4.5.6 Moderating Effect

The moderating effect analysis examines whether INNOV alters the strength of the relationships between the TOE factors and the IABD. The interaction terms were assessed to determine which technological, organisational, and environmental factors are significantly influenced by the level of innovativeness within SMEs, as presented in Table 4.19.

Table 4.19
Moderating Effects of Organisational Innovativeness on TOE Factors and IABD

Path	beta	SE	T Statistics	P Values
RADV * INNOV-> IABD	0.103	0.038	2.690	0.007
COMP * INNOV -> IABD	0.027	0.032	0.835	0.404
CMPLX * INNOV -> IABD	0.042	0.034	1.241	0.215
TR * INNOV -> IABD	0.046	0.030	1.556	0.120
OB * INNOV -> IABD	-0.043	0.033	1.325	0.186

TMS * INNOV -> IABD	0.002	0.025	0.072	0.942
OR* INNOV -> IABD	0.086	0.028	3.051	0.002
COMPR* INNOV -> IABD	0.108	0.032	3.362	0.001
EXSUPP * INNOV -> IABD	0.038	0.031	1.242	0.215
GOVS * INNOV -> IABD	-0.050	0.036	1.373	0.171

The structural model illustrates the relationships between the technological, organisational, and environmental factors and the IABD after incorporating the moderating effect of INNOV. The paths indicate the direct effects of the TOE variables on adoption intention, while the additional interaction paths represent the moderating influence of innovativeness on these relationships. The figure also displays the factor loadings of the measurement items and the path coefficients between constructs, demonstrating how certain TOE factors retain stronger explanatory power when INNOV is considered. This integrated representation clarifies both the measurement and structural components of the model in a single framework, as shown in Figure 4.2.

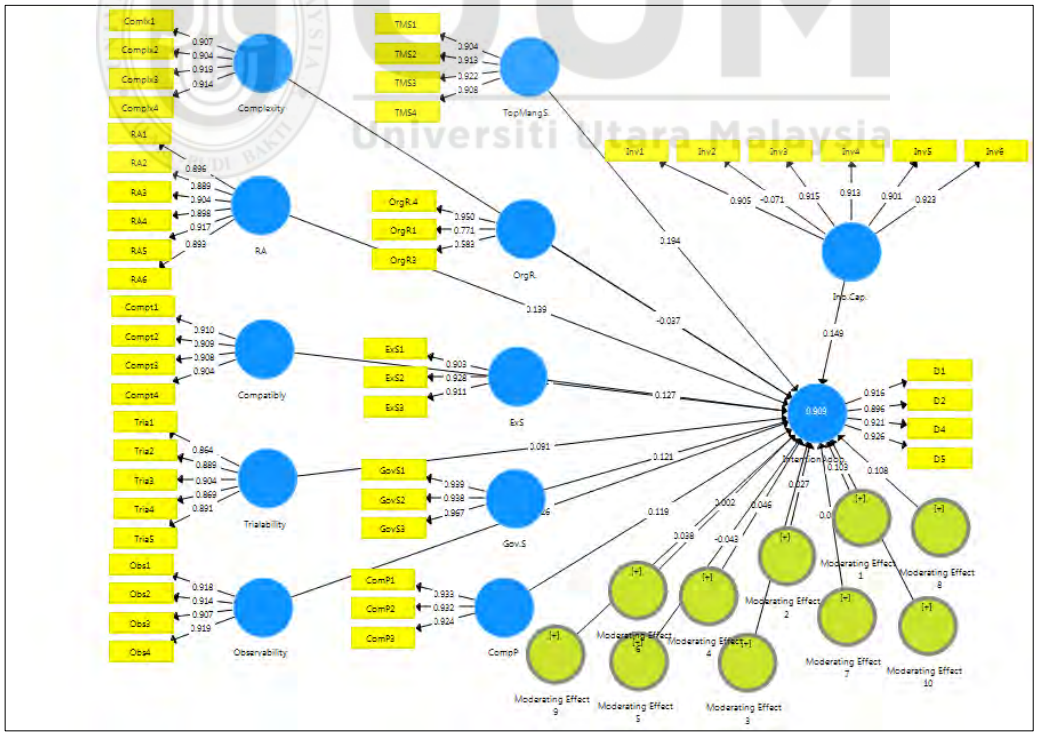


Figure 4.2
Results of the First Structural Model (After Moderation)

4.6 SUMMARY

This chapter discuss the empirical analysis was conducted and the results were presented. This empirical analysis was to test research hypothesis in this study represented by the casual structural model. The model was tested with two-step SEM including the measurement and structural model. Before conducting this analysis, the data screened for normality. Additionally, hypothesis testing and moderating effect were presented which revealed three out of tenth were supported and seven was not supported (Refer to Table 4.21). A detailed discussion and finding from the analysis are further discussed in the next chapter.

Universiti Utara Malaysia

Table 4.20
Summary of Hypotheses Testing (Main Effects Model)

Code	Hypotheses	Predict Sign	Findings
	Direct Relationships		
	Technological Context		
H1	Relative Advantage influences the Intention to adopt Big Data	+	supported
H2	Compatibility influences the Intention to adopt Big Data	+	supported
H3	Complexity influences the Intention to adopt Big Data	-	supported
H4	Trialability influences the Intention to adopt Big Data	+	supported
H5	Observability influences the Intention to adopt Big Data	+	supported
	Organisational Context		
H6	Top management support influences the Intention to adopt Big Data	+	supported
H7	Organisational readiness influences the Intention to adopt Big Data	+	Not supported
	Environmental Context		
H8	Competitive pressure influences the Intention to adopt Big Data	+	Not supported
H9	External support from vendors influences the Intention to adopt Big Data	+	supported
H10	Governmental support influences the Intention to adopt Big Data	+	supported

Table 4.21
Summary of Hypotheses Testing (Moderating Effects)

Code	Hypotheses	Predict Sign	Findings
	Moderating Effects		
H11a	Innovation of organisations moderates the relationship between Relative Advantage and Intention to adopt Big Data.	+	Supported
H11b	Innovation of organisations moderates the relationship between Compatibility and Intention to adopt Big Data.	+	Not supported
H11c	Innovation of organisations moderates the relationship between Complexity and Intention to adopt Big Data.	+	Not supported
H11d	Innovation of organisations moderates the relationship between Trialability and Intention to adopt Big Data.	+	Not supported
H11e	Innovation of organisations moderates the relationship between Observability and Intention to adopt Big Data.	+	Not supported
H11f	Innovation of organisations moderates the relationship between Top Management Support and Intention to adopt Big Data.	+	Not supported
H11g	Innovation of organisations moderates the relationship between Organisational Readiness and Intention to adopt Big Data.	+	Supported
H11h	Innovation of organisations moderates the relationship between Competitive pressure and Intention to adopt Big Data.	+	Supported
H11j	Innovation of organisations moderates the relationship between External support from vendors and Intention to adopt Big Data.	+	Not supported
H11k	Innovation of organisations moderates the relationship between Governmental support and Intention to adopt Big Data.	+	Not supported

Universiti Utara Malaysia

CHAPTER 5

DISCUSSION, IMPLICATION AND CONCLUSION

5.1 Introduction

This final chapter presents the study's findings and is structured around the objectives that guided the research. The study encompassed four objectives and eleven hypotheses, with a particular focus on the moderating effect of INNOV on the relationship between technological, organisational, and environmental factors and the IABD among SMEs in Palestine.

This Chapter has six sections. Aside from this introductory section 5.1, the second section 5.2 deals with the recapitulation of the study. The third section 5.3 discusses the findings of the research. This section has four subsections, each subsection discusses the relationship between the variables under examination based on each research objective. The fourth section 5.4 explains the implications of the study comprising the theoretical and practical implications. The fifth section 5.5 discusses the limitations of the study and suggestions for future studies, finally the last section 5.6 concludes the study.

Universiti Utara Malaysia

5.2 Recapitulation of the Study

The low rate of BDA has encouraged extensive research into the factors that influence this decision. However, prior empirical findings remain inconsistent. To address this gap, the present study was guided by four research questions and corresponding objectives focusing on the relationships between RA, COMP, CMPLX, TR, and OB; TMS and OR; and COMPR, EXSUPP, and GOVS and IABD among SMEs in

developing economies, including Palestine, as well as the moderating role of INNOV in these relationships. Accordingly, the study aimed to examine the direct relationships between these TOE factors and IABD and to assess how INNOV moderates these relationships within the Palestinian SME context.

This study focused on the IABD technologies in SMEs. Unlike previous research that explored the actual use of BD, this study emphasizes the pre-adoption phase and early stages of implementation. Understanding these stages provides insights into the initial barriers and motivators that SMEs face. The study employs a combined TOE and DOI framework.

For instance, Trisnadewi et al. (2024) used TOE to explore BD analytics adoption in SMEs, identifying technological readiness, organisational support, and environmental pressure as key factors. Similarly, Alshamaila et al. (2013) utilized both TOE and DOI to study cloud computing adoption in SMEs, emphasizing perceived benefits, COMP, and external pressures. These studies focused on actual adoption rather than the intention to adopt.

Universiti Utara Malaysia

By examining both the intention and early stages of adoption, this study aims to fill a critical gap in the literature. The insights gained will help policymakers and business leaders design strategies to encourage BDA among SMEs, which often face unique challenges due to limited resources.

The study proposed a comprehensive model to examine the adoption of BD in SMEs. This model integrated the TOE and DOI frameworks within one theoretical framework, analyzing the impact of various factors such as technological context (RADV, COMP, CMPLX, TR, OB), organisational context (TMS, OR), and

environmental context (COMPR, EXSUPP, GOVS) on the IABD. Additionally, the study incorporated INNOV as a moderating variable within one theoretical framework. To address the existing gap, the study investigated the factors influencing the IABD, aiming to encourage SMEs in Palestine to leverage BD technologies to enhance their performance and maintain competitiveness in both local and global markets. By combining the TOE and DOI frameworks, the study examined the moderating role of INNOV in shaping the relationship between these factors and the IABD among Palestinian SMEs.

As mentioned in Chapter Three, data were gathered from Palestinian SME managers. A questionnaire was administered to specific SMEs located in the Gaza Strip, Palestine, to assess the hypotheses formulated in this study. The targeted areas for data collection included North Gaza, Gaza, Middle District, Khan Yunis, and Rafah. In line with these guidelines, 533 questionnaires were distributed among owners and managers of Palestinian SMEs operating in various sectors within the Gaza Strip using the simple random sampling technique. Of the distributed questionnaires, 272 responses were deemed suitable for inclusion in the analysis, recording a response rate of 60.44%.

This comprehensive data collection process ensured a representative sample, allowing for robust analysis and reliable conclusions regarding the factors influencing the IABD technologies among SMEs in Palestine.

All latent variables utilised in this study were validated to ensure both reliability and validity. The results demonstrated an acceptable level of these metrics, enabling further analysis. Moreover, the data revealed that the total variance in BDA accounted

for 90.9%, indicating that the nine sets of exogenous latent constructs collectively explained this variance in BDA.

The data were analysed using SmartPLS version 3.2 to test the hypothesized associations in the structural model of the study. Among the different significance levels available to researchers, this study used the 0.05 level of significance to determine whether to reject or accept the hypotheses. The findings have shown that among the three contextual factors, i.e., technological, organisational, and environmental, the technological context is the most salient in influencing BDA. Specifically, RADV was found to have the strongest effects based on the coefficient value on the adoption of BD among all factors being examined. Meanwhile, the environmental context emerged as the next most important contextual factor as represented by GOVS. Finally, the organisational context was the least important contextual factor with the lowest coefficient value.

Universiti Utara Malaysia

The findings have shown that the effects of RADV, COMP, CMPLX, TR, OB, TMS, EXSUPP, and GOVS on BDA were supported, while OR and COMPR were not. The findings also indicated that the effect of INNOV on BDA was supported.

Regarding the moderating effect of INNOV, the findings have shown that it played a significant role in the relationship between several contextual factors and BDA. Specifically, INNOV significantly moderated the effects of RADV, OR, and COMPR on BDA. The results of the analysis were reported in Chapter Four and will be further discussed in more detail in the following sub-sections.

5.3 Discussion of Findings

This section examined the study's results in the context of underpinning theories and prior research findings. The subsequent subheadings in the discussion section were organized around the research questions established earlier, analyzing the results in relation to the study's objectives.

5.3.1 Technological Context

The technological context within the TOE framework and the factors included in the current study's research model were discussed in section 3.2. This study builds upon previous research that identified significant technological factors influencing adoption decisions, particularly focusing on those proposed by the DOI theory: RADV, COMP, CMPLX, TR, and OB (Rogers, 2003; Yadegaridehkordi et al., 2020).

In accordance with the DOI theory, this research found that RADV and COMP significantly influence the IABD among Palestinian SMEs. The results revealed that COMP had the strongest effect on BDA, indicating that when the technology aligns well with existing business processes and values, SMEs are more likely to adopt it. This finding is consistent with recent studies that highlight the importance of COMP in technology adoption (Verma & Chaurasia, 2019; Maroufkhani et al., 2020a).

RADV also played a crucial role, as SMEs perceived the tangible benefits of BD, such as improved decision-making and operational efficiency, as significant motivators for adoption. This aligns with the findings of Yadegaridehkordi et al. (2020), who emphasized the role of perceived benefits in technology adoption.

Universiti Utara Malaysia

CMPLX was found to have a significant impact on the IABD, aligning with the findings of other studies that have identified CMPLX as a barrier to adoption (Verma & Chaurasia, 2019; Sam & Chatwin, 2019). This suggests that the perceived difficulty in understanding and using BD technologies can hinder their adoption by SMEs.

Trialability and OB were also found to have a significant impact on the IABD among Palestinian SMEs. This may be due to the opportunity for SMEs to experiment with BD solutions and observe their use in similar organisations, which can enhance their confidence in the adoption process (Maroufkhani et al., 2020b; Jang et al., 2019).

In summary, the study validates the relevance of the DOI theory in explaining BDA among Palestinian SMEs, particularly highlighting the pivotal roles of RADV, COMP, CMPLX, TR, and OB. The integration of the TOE framework with the DOI theory provides a comprehensive understanding of the factors influencing BDA. This combination allows for a detailed analysis of both internal organisational factors and external environmental pressures, leading to more effective strategies for promoting BDA. The following subsections provide a detailed discussion of each technological factor examined in this study.

Universiti Utara Malaysia

5.3.1.1 The Influence of Relative Advantage on IABD in SMEs

The first objective of this study was to assess the influence of RADV on the IABD among Palestinian SMEs. The analysis of the collected data, in alignment with the first research question, revealed that RADV plays a significant and positive role in shaping this intention. These findings confirm that SMEs are more likely to adopt BD when they perceive clear operational and strategic benefits, such as improved decision-making, efficiency, and competitiveness. This result provides empirical support for

H1, which hypothesised a positive relationship between RADV and IABD.

This result aligns with the DOI theory, which asserts that the greater the perceived advantage of an innovation, the higher the likelihood of its adoption (Rogers, 2003). The current study empirically supports this theoretical prediction, demonstrating that Palestinian SMEs perceiving BD as offering substantial benefits are more inclined to integrate these technologies into their operations.

However, the findings also indicate that not all SMEs perceive these advantages equally. The variation in perception is influenced by OR, technological infrastructure, and managerial awareness. SMEs with strong digital infrastructure and better IT capabilities were more responsive to BD's potential benefits, while those with limited resources and low awareness showed weaker intentions. This suggests that the perceived advantage of BD is context-dependent, shaped by a firm's internal capacity to recognize and utilise its potential (Chuah & Thurusamry, 2021; Lutfi et al., 2022b).

Universiti Utara Malaysia

In the Palestinian context, where SMEs face structural and resource constraints, perceived advantage becomes meaningful only when accompanied by support mechanisms that reduce uncertainty such as vendor training, government incentives, and observable success stories (Baig et al., 2023; Nasrollahi et al., 2021). Competitive signals and vendor assurances can also amplify perceived advantages by demonstrating BD's practical value and return on investment. Conversely, when uncertainty remains high due to cost, CMPLX, or limited technical expertise, the influence of RADV on adoption intention weakens.

These findings help explain why some earlier studies have reported inconsistent results (Maroufkhani et al., 2020b; Nam et al., 2015), emphasizing that RADV alone is not

sufficient; it must be credible, visible, and achievable for firms to act upon it.

In conclusion, the study confirms that RADV is a key determinant of BDA intention among Palestinian SMEs. Firms that clearly recognize BD's contribution to decision-making, efficiency, and competitiveness are more inclined to adopt it. Nonetheless, this advantage is strengthened when combined with adequate readiness, infrastructure, and external support. Therefore, both policymakers and vendors should focus on enhancing SMEs' technological awareness, providing low-risk trials, and developing supportive initiatives that make BD's benefits more visible and attainable. Such efforts can foster a more data-driven and competitive SME sector in developing economies.

5.3.1.2 The Influence of Compatibility on IABD in SMEs

The second research objective examined whether COMP significantly influences the IABD among Palestinian SMEs. The results indicated that COMP had a positive and significant effect, confirming that when BD is perceived as compatible with existing systems, culture, and operational processes, firms are more inclined to adopt it. This supports the study's second hypothesis and aligns with the core proposition of the DOI framework that innovations fitting current values and practices face less resistance and are more readily accepted (Rogers, 2003).

The findings reinforce that alignment between BD tools and existing workflows enhances adoption by minimizing operational disruption and employee resistance. SMEs that viewed BD as consistent with their current infrastructure and managerial routines demonstrated higher adoption intentions, as COMP facilitates integration and reduces perceived complexity (Mahesh et al., 2018; Verma & Chaurasia, 2019). This is particularly relevant for SMEs, where streamlined operations and resource

efficiency are essential for survival.

However, the strength of COMP's influence varied across firms, reflecting differences in technological readiness, digital literacy, and awareness of BD's potential (Chuah & Thurusamry, 2021; Lutfi et al., 2022b). SMEs with well-developed IT infrastructure and digitally aware management teams were more capable of recognizing COMP benefits, while resource-constrained firms found it difficult to envision how BD could be incorporated into their operations. This suggests that COMP perception is not purely technical but also cognitive and organisational, depending on the firm's ability to integrate and interpret new technologies.

In the Palestinian context, where SMEs face persistent financial and infrastructural challenges, COMP becomes critical in reducing implementation barriers. When BD applications align with existing technological setups and operational norms, the need for costly restructuring or specialized training is minimized, thereby lowering adoption resistance. Nonetheless, the results indicate that COMP's effect is contingent on other contextual factors such as managerial innovativeness and organisational support. Firms with innovative leaders were better able to adapt BD solutions to their operational realities, making COMP a dynamic, rather than static, construct.

Universiti Utara Malaysia

In conclusion, the study confirms that COMP is a crucial determinant of BDA intention among Palestinian SMEs. The findings emphasize that BDA success depends not only on the technology's fit with existing systems but also on the organisation's adaptive capacity and managerial vision. Policymakers and vendors should therefore design BD tools that integrate easily with SMEs' current operations and provide training to enhance digital awareness. This alignment between technology and organisational

context will enable smoother adoption and strengthen the overall digital transformation of SMEs in developing economies.

5.3.1.3 The Influence of Complexity on IABD in SMEs

The third research objective examined the effect of CMPLX on the IABD among Palestinian SMEs. The results showed that CMPLX had a negative and significant influence on adoption intention, supporting the third hypothesis and the DOI assumption that higher perceived complexity reduces the likelihood of adoption (Rogers, 2003).

The findings confirm that SMEs perceiving BD as difficult to understand or implement are less likely to adopt it. This perception stems from challenges such as the lack of standardized tools, integration difficulties with existing systems, and high costs related to technical expertise and infrastructure (Agrawal, 2015; Verma & Chaurasia, 2019). These results are consistent with prior studies in India, Malaysia, and Jordan, which identified CMPLX as a key barrier to BDA (Baig et al., 2023; Lutfi et al., 2022b).

However, the study also revealed that the negative effect of CMPLX is not uniform across all firms. SMEs with greater technological readiness, higher digital literacy, and better vendor or governmental support were less affected by perceived complexity. For these firms, access to training, consultation, and support services helped mitigate technical difficulties and reduce uncertainty, making adoption more feasible (Park & Kim, 2021; Sam & Chatwin, 2019). Conversely, firms with weak IT infrastructure and limited resources reported higher levels of CMPLX, which discouraged them from exploring BD initiatives (Nasrollahi et al., 2021).

Universiti Utara Malaysia

In the Palestinian context, CMPLX perception is intensified by structural and environmental challenges, including limited internet infrastructure, financial constraints, and a shortage of skilled data professionals. These conditions increase implementation risks and operational uncertainty, causing many SMEs to perceive BD as overly demanding. Nonetheless, where INNOV and managerial competence were higher, SMEs showed greater adaptability, suggesting that internal innovation culture can offset part of the negative influence of CMPLX.

In conclusion, the study confirms that CMPLX is a critical inhibitor of BDA intention among Palestinian SMEs. Reducing perceived CMPLX requires targeted interventions that strengthen SMEs' technological readiness and provide accessible training and vendor assistance. Policymakers and vendors should focus on simplifying BD applications, offering localized support programs, and promoting pilot implementations to build user confidence. These initiatives can make BD technologies more approachable, ultimately enabling broader adoption among SMEs operating under constrained conditions.

5.3.1.4 The Influence of Trialability on IABD in SMEs

The fourth research objective explored the impact of TR on the IABD among Palestinian SMEs. The results revealed that TR had a positive and significant effect on adoption intention, confirming the fourth hypothesis and aligning with the DOI principle that the ability to experiment with an innovation reduces uncertainty and strengthens adoption likelihood (Rogers, 2003).

The findings indicate that SMEs able to test or pilot BD tools before full-scale implementation are more confident in their decisions to adopt. This opportunity to

experiment allows managers to evaluate the practical benefits, identify integration challenges, and minimize risks related to cost and performance uncertainty (Alshamaila et al., 2013; Priyadarshinee et al., 2017). Consequently, firms that engage in small-scale trials develop stronger trust in technology's value and COMP with existing processes.

However, the study also highlights that the availability of trial opportunities varies significantly among SMEs. In Palestine, limited EXSUPP, inadequate infrastructure, and financial constraints reduce access to pilot implementations or free trial versions. These barriers prevent firms from gaining first-hand experience with BD tools, thereby sustaining uncertainty and slowing adoption. This observation helps explain why some studies reported weaker effects of TR (Sun et al., 2018; Yadegaridehkordi et al., 2018), as the absence of trial mechanisms diminishes the perceived feasibility of adoption.

SMEs with higher technological readiness and external support for example, from vendors or government agencies, perceive lower risks and stronger benefits from experimenting with BD (Maroufkhani et al., 2020b; Sharma et al., 2023). Conversely, resource-constrained firms lacking technical assistance face greater hesitation, often deferring adoption until clearer evidence or demonstrations of success become available.

In the Palestinian context, promoting TR is especially critical. Structured pilot programs and vendor-led demonstrations can provide SMEs with experiential learning opportunities, reduce the fear of failure, and foster managerial confidence in BD's potential. By lowering uncertainty and perceived CMPLX, such initiatives can transform BD from a high-risk investment into an achievable innovation goal.

Universiti Utara Malaysia

In conclusion, the study confirms that TR is a vital enabler of BDA intention among Palestinian SMEs. Facilitating trial opportunities through pilot projects, EXSUPP, or government-backed initiatives can help firms evaluate the tangible value of BD, reduce uncertainty, and promote broader adoption. These results emphasize that hands-on experimentation is not merely a preliminary step but a strategic mechanism that builds trust, learning, and long-term innovation capacity among SMEs.

5.3.1.5 The Influence of Observability on IABD in SMEs

The fifth research objective examined the influence of OB on the IABD among Palestinian SMEs. The results showed that OB had a positive and significant effect on adoption intention, supporting the fifth hypothesis and the DOI proposition that greater visibility of innovation outcomes enhances adoption likelihood (Rogers, 2003).

The findings indicate that SMEs that can observe the successful use and benefits of BD in other firms such as improved efficiency, customer insight, and competitiveness develop higher confidence in its value and are more inclined to adopt it. This aligns with previous studies suggesting that observable success stories reduce uncertainty and serve as persuasive evidence of BD's practicality and profitability (Mahesh et al., 2018; Sam & Chatwin, 2019; Yadegaridehkordi et al., 2018).

However, the effect of OB was found to depend on information accessibility and inter-firm interaction. SMEs that operate within active business networks or industry associations have more opportunities to witness or learn from others' BD initiatives, which strengthens their perception of feasibility. Conversely, in contexts like Palestine where collaboration and communication among firms are often limited the visibility

Universiti Utara Malaysia

of innovation outcomes remains low. This lack of demonstrable examples reduces peer learning and weakens the motivational power of OB in driving adoption.

Additionally, trust in information sources plays an essential role. When observable results are shared through credible channels such as vendor case studies, local workshops, or government-sponsored innovation programs, SMEs are more likely to interpret them as reliable indicators of BD's success. In contrast, where examples are anecdotal or poorly communicated, the motivational influence of OB diminishes.

The findings thus reveal that OB functions not only as a visibility factor but also as a social learning mechanism. It enables SMEs to infer potential benefits by observing others' experiences, reducing uncertainty before committing resources. To leverage this effect, policymakers and technology providers in Palestine should facilitate knowledge-sharing platforms, industry exhibitions, and local success stories that showcase concrete outcomes of BD implementation.

Universiti Utara Malaysia

In conclusion, the study confirms that OB is a significant enabler of BDA among Palestinian SMEs. By enhancing visibility, promoting inter-firm communication, and disseminating credible evidence of BD's benefits, stakeholders can build a stronger perception of value and reliability. Such initiatives will encourage hesitant SMEs to transition from observation to adoption, contributing to a more innovative and data-driven business ecosystem.

5.3.2 Organisational Context

The organisational context within the TOE framework is critical in influencing the adoption of BD among Palestinian SMEs. This section examines the impact of

organisational factors, particularly focusing on TMS and OR. The organisational context includes the internal characteristics and resources of the firm that facilitate or constrain the adoption of new technologies (Tornatzky & Fleischer, 1990).

Top management support is essential for the successful adoption of BD. Studies have shown that strong managerial backing can significantly influence the adoption process by ensuring the necessary resources and fostering a culture that embraces innovation (Lai et al., 2018; Lutfi et al., 2022a). When top management is committed to providing financial, technical, and human resources, the challenges associated with BDA can be effectively addressed (Park & Kim, 2021).

Organisational readiness, which includes the availability of necessary resources and the overall preparedness of the organisation to implement new technologies, also plays a pivotal role in BDA. Organisational readiness encompasses technological infrastructure and employee skills, which are crucial for the successful integration of BD analytics (Rajabion, 2018; Sun et al., 2018).

Universiti Utara Malaysia

In summary, the study highlights the importance of the organisational context, particularly TMS and OR, in influencing the IABD among Palestinian SMEs. The following subsections provide a detailed discussion of each organisational factor examined in this study.

5.3.2.1 The Influence of Top Management Support on IABD in SMEs

The sixth research objective aimed to assess the influence of TMS on the intention to adopt BD among Palestinian SMEs. The results demonstrated that TMS had a positive and significant effect on adoption intention, supporting the sixth hypothesis and

aligning with the TOE framework, which highlights management support as a key organisational driver of technological innovation (Tornatzky & Fleischer, 1990).

The findings confirm that SMEs with committed and proactive top management are more likely to adopt BD technologies. When leaders allocate financial, technical, and human resources and actively promote innovation, they create a culture that facilitates technological integration and reduces resistance to change (Lai et al., 2018; Lutfi et al., 2022b). In resource-constrained environments such as Palestine, managerial support becomes particularly vital to overcoming challenges such as financial limitations, poor infrastructure, and restricted access to modern technology.

While prior research consistently identifies TMS as a central determinant of adoption (Jang et al., 2019; Sharma et al., 2023), this study reinforces that its effect extends beyond resource provision it also shapes employees' confidence and readiness to engage with BD. SMEs whose leaders communicate a clear innovation vision tend to experience smoother implementation and stronger commitment from staff, leading to higher adoption intentions (Park & Kim, 2021; Gangwar, 2018).

Universiti Utara Malaysia

However, the findings also suggest that the strength of TMS may vary depending on organisational context. In smaller or less formalized firms, decision-making may be decentralised, or managers may lack the expertise needed to support BD initiatives effectively (Lindawati et al., 2023). In such cases, external support from vendors or training institutions can complement managerial efforts, ensuring sufficient guidance throughout the adoption process.

In the Palestinian context, where SMEs operate under continuous economic and infrastructural constraints, managerial leadership acts as a substitute for institutional

support. Leaders who can mobilize resources, encourage collaboration, and sustain morale despite uncertainty play a decisive role in determining whether BD projects move beyond intention to actual implementation.

In conclusion, this study confirms that TMS is a critical enabler of BDA intention among Palestinian SMEs. Strong leadership commitment not only ensures access to resources but also builds a culture of confidence and adaptability necessary for successful innovation. Encouraging managers to engage directly with BD initiatives through capacity building, partnerships, and clear strategic alignment will be essential for fostering data-driven transformation and enhancing the long-term competitiveness of SMEs.

5.3.2.2 The Influence of Organisational Readiness on IABD in SMEs

The seventh research objective examined the influence of OR on the IABD among Palestinian SMEs. The results revealed that OR did not have a significant effect on adoption intention, contrary to the general expectation of the TOE framework, which assumes that higher readiness facilitates technological adoption (Tornatzky & Fleischer, 1990).

This finding contrasts with several previous studies that identified OR as a critical determinant of BDA in SMEs (Baig et al., 2023; Lutfi et al., 2022b; Yadegaridehkordi et al., 2020). However, it aligns with studies such as Angwar (2018) and Maroufkhani et al. (2023), which reported that OR may lose its influence once firms reach a minimum technological maturity or compensate for limited internal resources through external support.

The results indicate that OR alone may not determine BDA in environments where external, structural, and political barriers dominate. In Palestine, SMEs operate under conditions of restricted infrastructure, financial constraints, and limited access to skilled IT professionals. The blockade on Gaza and the absence of modern communication networks (3G, 4G, and 5G) hinder firms' ability to upgrade systems and maintain digital operations. Under such constraints, the perceived benefits of readiness technological infrastructure, financial resources, and human expertise are overshadowed by external limitations beyond managerial control.

This context suggests that managerial adaptability and external collaboration may substitute for traditional readiness. SME leaders who can secure partnerships, attract international support, or engage vendors effectively can mitigate the lack of internal infrastructure. In such cases, OR becomes less a matter of available resources and more a reflection of strategic capability and leadership resilience.

Universiti Utara Malaysia

The findings also imply that TOE's assumption of internal readiness as a direct determinant may not fully apply in conflict-affected economies. Here, environmental factors political instability, market fragmentation, and resource scarcity play a greater role in shaping adoption outcomes. Therefore, readiness in the Palestinian context must be understood as relative and externally contingent, rather than purely internal and resource-based.

In conclusion, while OR is theoretically crucial to technology adoption, this study demonstrates that in fragile economic and political environments like Palestine, its direct effect on adoption intention is limited. The finding highlights the importance of expanding the TOE framework to include contextual moderators such as

environmental volatility and institutional dependency that redefine how OR functions under constraint. For policymakers and managers, enhancing readiness will thus require not only internal investment but also systemic reforms and sustained external support to overcome structural barriers to BDA.

5.3.3 Environmental Context

The environmental context within the TOE framework pertains to the external conditions under which organisations operate and offer their services. This context includes factors such as COMPR, EXSUPP, and GOVS, which can significantly influence the adoption of BD among SMEs. The environmental context is crucial as it can both constrain and provide opportunities for technological innovations (Tornatzky & Fleischer, 1990).

Competitive pressure refers to the influence exerted by competitors, customers, and suppliers that can drive SMEs to adopt BD technologies. When SMEs perceive that their competitors are successfully leveraging BD, they may feel compelled to adopt similar technologies to remain competitive. This factor has been highlighted in various studies, emphasizing its role in motivating technology adoption (Sun et al., 2020; Verma & Chaurasia, 2019).

External vendor support involves the assistance provided by third-party vendors in the adoption and implementation of BD technologies. This support can include training, technical assistance, and consultancy services, which are vital for SMEs that may lack the internal expertise to implement BD solutions effectively. Studies have shown that strong EXSUPP can facilitate the adoption process by reducing perceived risks and complexities (Maroufkhani et al., 2020b; Gangwar, 2018).

Government support includes policies, incentives, and regulatory frameworks that encourage the adoption of big data technologies. Government initiatives can provide financial incentives, training programs, and infrastructure development that support SMEs in adopting innovative technologies. The role of GOVS in technology adoption has been well-documented, highlighting its importance in creating a conducive environment for innovation (Park & Kim, 2021; Angwar et al., 2018).

In summary, the study highlights the significant role of the environmental context in influencing the IABD among Palestinian SMEs. The following subsections provide a detailed discussion of each environmental factor examined in this study.

5.3.3.1 The Influence of Competitive Pressure on IABD in SMEs

The eighth research objective aimed to examine the influence of COMPR on the intention to adopt big data among Palestinian SMEs. The results revealed that COMPR did not have a significant effect on adoption intention, diverging from the TOE framework's assumption that external competitive forces drive firms to adopt technological innovations (Tornatzky & Fleischer, 1990).

This finding challenges the pattern observed in many international studies, where competitive intensity encourages firms to adopt BD to improve efficiency and sustain advantage (Jang et al., 2019; Sun et al., 2020; Yadegaridehkordi et al., 2020). Instead, it aligns with the results of Angwar (2018) and Maroufkhani et al. (2023), who found that in contexts characterised by economic fragility or weak market integration, competitive pressure exerts little to no influence on adoption behaviour.

In the Palestinian context, this non-significance can be explained by structural and

environmental constraints that overshadow market dynamics. SMEs face severe financial shortages, inadequate ICT infrastructure, and restricted access to advanced technologies due to the blockade and ongoing political instability. These constraints hinder firms' ability to compete technologically, making survival rather than competition the primary strategic concern. When basic resources are scarce, SMEs tend to prioritise sustaining operations over pursuing competitive advantages through costly innovations like BD.

Furthermore, limited market visibility and low diffusion of success stories reduce the motivational effect of competition. Many SMEs operate in localised, fragmented markets with little exposure to international technological benchmarks. Consequently, the perceived need to adopt BD for competitive parity remains weak, as firms rarely witness tangible performance gaps that compel innovation. This pattern aligns with observations by Jang et al. (2019), who argued that visible examples of successful adoption are critical for competition-driven innovation diffusion.

Another plausible interpretation is that the Palestinian BDA landscape is still in its early stage of awareness rather than competitive acceleration. At this formative stage, internal enablers such as TMS and perceived RADV are more decisive than external rivalry. Only once BDA becomes more widespread and visible will competitive forces likely emerge as a stronger motivator.

In short, while COMPR is theoretically positioned as an important driver within the TOE framework, the findings from this study demonstrate that its influence is highly context-dependent. In unstable and resource-limited economies, external pressure alone is insufficient to trigger technology adoption without parallel improvements in

infrastructure, policy stability, and vendor support.

In conclusion, the results underscore that COPMR does not currently shape BDA decisions among Palestinian SMEs. To activate the role of competition as a driver, stakeholders must first strengthen market conditions and technological foundations. Building infrastructure, enabling access to modern communication technologies, and showcasing local success stories could gradually heighten competitive dynamics and transform BDA from a strategic choice into an operational necessity.

5.3.3.2 The Influence of External Vendor Support on IABD in SMEs

The ninth research objective examined the influence of EXSUPP on the IABD among Palestinian SMEs. The results revealed that EXSUPP had a positive and significant effect on adoption intention, supporting the ninth hypothesis and aligning with the TOE framework, which recognises external assistance as a key enabler of technological innovation (Tornatzky & Fleischer, 1990).

Universiti Utara Malaysia

The findings confirm that SMEs receiving continuous and high-quality EXSUPP such as technical guidance, software maintenance, and tailored training are more likely to adopt BD technologies. Vendors serve as critical partners who compensate for SMEs' limited internal IT expertise and resource constraints by providing accessible technical knowledge and problem-solving services (Nguyen et al., 2022). This external collaboration helps firms mitigate the perceived risks of BD implementation and enhances their confidence in managing technological change.

Consistent with prior studies (Gangwar, 2018; Yadegaridehkordi et al., 2020; Nasrollahi et al., 2021), the results show that EXSUPP not only reduces complexity

and costs but also improves firms' operational readiness by facilitating smoother integration and post-adoption maintenance. In environments where internal IT capability is weak, such as in many Palestinian SMEs, vendors play a bridging role providing scalable, affordable, and context-specific solutions that enable firms to participate in digital transformation despite limited internal resources.

The significance of EXSUPP in the Palestinian context is particularly pronounced due to restricted access to advanced technologies and frequent infrastructural disruptions. Local vendors often act as intermediaries between SMEs and global technology providers, offering adapted systems, localised training, and affordable service packages. This adaptive approach aligns with the TOE framework's assertion that effective external partnerships can offset internal weaknesses and promote technological adoption.

Universiti Utara Malaysia

However, the study also highlights a potential area for improvement: the need for sustained and localised vendor ecosystems. Many SMEs still depend on external agents or regional suppliers, whose support may not fully address Palestine's unique infrastructural and regulatory constraints. Strengthening local vendor capacity and encouraging public–private partnerships could improve continuity and reduce SMEs' dependence on external entities.

In conclusion, the study validates that EXSUPP is a critical determinant of BDA intention among Palestinian SMEs. Reliable vendor collaboration enhances confidence, reduces perceived complexity, and facilitates successful implementation. Policymakers and technology providers should therefore prioritise developing vendor–SME partnerships, establishing local support hubs, and offering flexible post-adoption

services. Such initiatives would enable SMEs not only to adopt BD effectively but also to sustain innovation and resilience in a challenging business environment.

5.3.3.3 The Influence of Government Support on IABD in SMEs

The tenth research objective explored the influence of GOVS on the IABD among Palestinian SMEs. The findings showed that GOVS had a significant and positive effect on adoption intention, supporting the tenth hypothesis and reinforcing the TOE framework's emphasis on the enabling role of external institutional support (Tornatzky & Fleischer, 1990).

The results confirm that when governments actively provide financial incentives, infrastructure support, and training initiatives, SMEs are more likely to embrace BD technologies. Such assistance reduces both perceived and actual barriers to adoption particularly those related to financial limitations, technical skills, and uncertainty surrounding data management (Nguyen et al., 2022; Park & Kim, 2021). This outcome is consistent with empirical evidence from prior research in China, Korea, Malaysia, and Jordan, where government-backed programs and policies significantly accelerated technology adoption in SMEs (Baig et al., 2023; Ghaleb et al., 2021; Lutfi et al., 2022b).

In the Palestinian context, the importance of GOVS is amplified by persistent structural and political challenges. SMEs operate under fragmented regulatory authorities, chronic resource shortages, and restricted access to global technology markets due to the blockade. These conditions magnify the value of any form of governmental facilitation be it tax incentives, subsidised ICT infrastructure, or partnerships with international development agencies. Government intervention can

thus function as a stabilising force, helping firms overcome the external shocks and institutional voids that typically hinder digital transformation.

However, the findings also imply that current government initiatives in Palestine remain limited and inconsistent, often constrained by financial instability, bureaucratic fragmentation, and competing political agendas. Weak coordination between central authorities and private-sector actors hampers the development of sustained digitalisation programs. Consequently, while the impact of GOVS is statistically significant, its practical effectiveness depends on the consistency and credibility of implementation rather than policy existence alone a distinction echoed by Maroufkhani et al. (2020).

To strengthen the ecosystem for BDA, the study recommends several measures: introducing targeted tax exemptions for technology-related investments, expanding national ICT training programs in partnership with universities, and developing data protection regulations to build organisational trust in digital systems. Additionally, inviting international experts to train SME clusters could foster local technical capacity and accelerate the diffusion of BD practices.

In conclusion, this study validates that GOVS is a key external driver of BDA among Palestinian SMEs, mitigating the constraints imposed by financial scarcity and infrastructural weakness. Yet, to sustain its positive influence, GOVS must evolve from sporadic assistance to a systematic innovation policy framework. A coordinated approach integrating financial incentives, capacity building, and regulatory assurance will be essential to transform SMEs' adoption of BD from isolated initiatives into a national driver of technological competitiveness and resilience.

Universiti Utara Malaysia

5.3.4 The Moderating Role of Organisational Innovativeness on Relationship between TOE Drivers and IABD in SMEs

The findings of this study provide substantial evidence that INNOV plays an important moderating role in shaping how SMEs interpret and respond to technological, organisational, and environmental factors related to BDA. INNOV defined as an organisation's openness to new ideas, experimentation, and creative problem-solving (Kirton, 2003; Marcati et al., 2008) has long been recognised as a key determinant of technological innovation.

Prior studies have similarly emphasised its role in enabling firms to adopt cloud computing (Alshamaila et al., 2013), the semantic web (Kim et al., 2018), blockchain technologies (Malik et al., 2021), and various ICT innovations (Asiaei & Ab. Rahim, 2019). The current findings extend this stream of knowledge by demonstrating that innovativeness not only influences adoption directly but also conditions how organisational and environmental factors operate in the context of BDA among Palestinian SMEs. This offers an important theoretical and empirical contribution, especially considering the inconsistent findings in BDA studies reported by Maroufkhani et al. (2020), Park and Kim (2021), and Nam et al. (2015).

The results reveal that INNOV significantly moderates the relationships between RADV, OR, and COMPR with the IABD. These findings align strongly with the DOI theory, which argues that organisations with higher innovativeness perceive innovations more positively and demonstrate greater readiness to explore and implement new technologies (Rogers, 2003).

For RADV, the results indicate that innovative firms derive greater value from BD

Universiti Utara Malaysia

solutions and are more capable of recognising their contribution to improved decision-making, operational efficiency, and long-term competitiveness. This is consistent with prior findings by Gangwar (2018) and Verma and Chaurasia (2019), who reported that innovativeness amplifies the perceived benefits of advanced digital tools. In this study, the moderating effect suggests that SMEs with a stronger innovative orientation are better positioned to identify and exploit the unique benefits of BD, making RADV a more compelling driver for adoption.

A similarly strong moderating effect was found between OR and the IABD. Although OR alone did not produce a significant direct effect, the interaction with INNOV revealed a significant and positive influence. This indicates that innovativeness enables organisations to overcome the readiness constraints that are typical in SMEs, such as limited technical skills, restricted financial resources, and the absence of sophisticated IT infrastructure (Ghobakhloo, 2011). This result reinforces arguments made by Yoon and George (2013) and Asiaei and Ab. Rahim (2019), who found that innovative organisations possess greater internal agility, making them more capable of mobilizing resources, training employees, and reengineering processes to support advanced technological adoption. Thus, in contexts where readiness alone is insufficient, INNOV acts as a catalyst that transforms a weak organisational foundation into a supportive platform for innovation.

The moderating effect of INNOV was also significant in the case of COPMR, reflecting findings from studies conducted in India, Malaysia, and other transitioning economies (Gangwar, 2018; Sun et al., 2020). Innovative organisations tend to be more sensitive and responsive to competitive dynamics. They are more aware of the strategic consequences of failing to keep pace with industry leaders and therefore are more

willing to adopt technologies such as BD to enhance their performance and maintain competitive relevance. This finding highlights a critical practical implication in environments characterized by intense competition and rapid technological change, SMEs need not only external pressure but an internal culture of innovativeness to respond effectively.

However, the moderating role of INNOV was not supported for other technological, organisational, and environmental factors such as COMP, CMPLX, TR, OB, TMS, EXSUPP, and GOVS. This suggests that these factors exert their influence independently of innovativeness, or that innovativeness alone is insufficient to strengthen or weaken their impact. For technological factors like COMP and CMPLX, non-significant moderation may reflect the inherently technical nature of these attributes, which are influenced more by system characteristics than by organisational culture (Maroufkhani et al., 2023; Chen et al., 2015). Similarly, TR and OB may depend more on market structures and vendor strategies than the organisation's internal innovativeness. For organisational support factors, such as TMS, the findings differ from some earlier studies (e.g., Lai et al., 2018; Park & Kim, 2021), indicating that within the Palestinian SME context, leadership commitment may already be uniformly high or uniformly constrained, making innovativeness less influential.

The absence of moderation for GOVS and EXSUPP may reflect structural challenges in emerging economies, where external support systems are often limited, inconsistent, or not sufficiently aligned with SME needs (Mneney et al., 2016; Maroufkhani et al., 2020b). In such cases, even innovative organisations may struggle to leverage external opportunities if systemic constraints such as inadequate technical infrastructure, weak institutional support, or limited specialized vendor services persist. This offers an

important contextual insight into the Palestinian SME environment and highlights potential areas for policy intervention.

Overall, the findings position INNOV as a crucial mechanism that activates or strengthens specific TOE relationships, particularly RADV, OR, and COMPR while exerting minimal influence on others. This provides empirical justification for integrating the TOE framework with DOI theory. TOE explains the structural, organisational, and environmental conditions shaping adoption, whereas DOI explains how innovation characteristics and innovativeness shape adoption behaviors. The moderating effect observed in this study demonstrates how innovativeness bridges these frameworks, producing a more comprehensive explanation of BDA dynamics. By clarifying why similar SMEs exposed to comparable contextual conditions may arrive at different adoption decisions, this study contributes a meaningful theoretical advancement. It also underscores the importance of cultivating an innovative culture within SMEs to fully realize the benefits of BD transformation an implication particularly relevant for Palestinian SMEs navigating economic constraints and technological uncertainty.

5.4 Implications for the Study and Practice of TOE Drivers on IABD

This study examined the technological, organisational, and environmental factors influencing the IABD among SMEs and further explored the moderating role of INNOV in these relationships. The findings offer important implications at three levels: the body of knowledge and theory, practitioners and policymakers, and society.

Universiti Utara Malaysia

5.4.1 Implications for the Body of Knowledge and Theory

This study provides substantial theoretical contributions by extending and integrating two well-established frameworks: the TOE framework and the DOI theory. The research advances the TOE framework by introducing INNOV as a moderating construct, offering a dynamic understanding of how technological, organisational, and environmental conditions shape the IABD. At the same time, the DOI theory is strengthened by empirically validating its innovation attributes RADV, COMP, CMPLX, TR, and OB at the organisational level within SMEs.

A key theoretical contribution lies in empirically validating an integrated TOE–DOI model, rather than examining the two frameworks independently as many previous studies have done. By demonstrating that INNOV moderates the relationships between selected TOE drivers (RADV, OR, and COMPR) and the IABD, this study explains inconsistencies noted in earlier research. This provides a novel analytical lens for understanding how internal innovative capabilities can amplify or diminish the effect of external conditions on technology adoption decisions.

Universiti Utara Malaysia

The contribution of this study is not limited to geographic context. Rather, its novelty lies in building and validating a comprehensive theoretical model that is generalisable across SMEs in different economic and cultural environments. By showing that the moderating role of innovativeness enhances the predictive power of TOE and DOI when combined, this study establishes a stronger theoretical foundation for examining technology adoption in resource-constrained organisations. It further enriches the literature by empirically testing relationships that were previously proposed

conceptually, thus bridging the gap between innovation theory and organisational practice.

5.4.2 Implications for Practitioners, Decision Makers, and Policy Makers

The findings also offer important practical implications for managers, decision makers, policymakers, and technology providers within and beyond the Palestinian context. For managers, the results highlight the critical importance of cultivating an innovative organisational culture that supports creativity, experimentation, and openness to new technologies. Since INNOV was found to significantly moderate the effect of RADV, OR, and COMPR, managers should invest in building internal innovation capabilities, encouraging employees to engage with digital tools, and reducing resistance to change.

Top management support remains essential in guiding digital transformation. Leaders should actively align BD initiatives with organisational strategies, allocate necessary financial and human resources, and champion data-driven decision-making. Doing so can help overcome common obstacles, such as limited technical expertise or financial constraints shared by SMEs globally.

For policymakers and government agencies, the findings reinforce the importance of designing supportive digitalisation policies, financial incentives, and capacity-building programs that strengthen SMEs' readiness for adopting emerging technologies. Governments can promote adoption by offering training programs, tax incentives, innovation grants, and forming partnerships with technology vendors to improve accessibility and affordability of BD solutions.

Universiti Utara Malaysia

Technology vendors and service providers also benefit from these insights by tailoring their solutions to SMEs' diverse needs. Providing scalable, cost-effective tools, trial versions, and continuous training can minimize perceived complexity and improve adoption rates. Success stories and case studies can serve as strategic tools for vendors to demonstrate BD's tangible value to SMEs.

Together, these practical implications contribute to a holistic roadmap for managers, policymakers, and technology providers seeking to accelerate BDA in SME ecosystems.

5.4.3 Implications for Society

Beyond academic and managerial contributions, this study offers broader societal implications. Big data adoption in SMEs can enhance economic resilience, improve service delivery, and generate employment opportunities by promoting digital skills development. In emerging economies such as Palestine, empowering SMEs to adopt big data can stimulate innovation across industries, strengthen competitiveness, and support national digital transformation efforts.

Moreover, the study highlights that fostering an innovative culture within organisations contributes to broader societal readiness for digital technologies. As SMEs make up a significant portion of the economy, increasing their digital capabilities can lead to more efficient markets, improved productivity, and enhanced public trust in technology. The findings also support the role of government in promoting equitable access to digital tools and capacity-building programmes, which can help bridge technological gaps across different communities.

Universiti Utara Malaysia

By enhancing decision-making, improving transparency, and supporting innovation-driven growth, big data adoption in SMEs contributes positively to economic development and societal well-being. This positions SMEs not only as economic actors but also as catalysts for broader societal progress in digital transformation.

5.5 Limitations and Future Research

Firstly, this study was conducted among various industries in Palestine, including agriculture, industry, construction, wholesale and retail trade, transportation and storage, information and communications, services, and other branches. Given Palestine's unique organisational culture and specific characteristics, coupled with ongoing conflict and instability, the findings may only be generalizable to firms in similar industries or countries experiencing comparable instability. Future research could benefit from replicating this study in different industries and countries. Such extensions could produce results that are similar or comparable, further enhancing our understanding of the usage and implications of BD. Testing the model in other national contexts would also help in validating the conceptualisations, measurement scales, and generalizability of the findings.

Secondly, this study focused on analysing the factors influencing BDA specifically within SMEs. It is important to note that these acceptance factors can vary based on industry characteristics. The influence of these factors may differ across manufacturing and service sectors, IT-related and non-IT firms, as well as technology-intensive and non-technology-intensive companies. Therefore, any generalisation of the findings should be approached with caution due to the differences in resources, capabilities, and systems among different developing countries and sectors. To gain a

deeper understanding of the acceptance process, future research should encompass comparative studies across industries.

Additionally, the acceptance factors of BD may differ between large enterprises and SMEs. SMEs typically have limited technical and financial resources, making government support and policies crucial for their adoption of BD. In contrast, internal collaboration and cultural factors may play a more significant role in driving BDA in large enterprises. Therefore, additional research is needed to understand the variations in acceptance factors based on firm size.

In future studies, scholars could explore alternative determinants or factors related to technology, organisation, and the environment, as the TOE model offers flexibility. By selectively including or excluding elements that align with the specific context of their studies, researchers can yield diverse results that accommodate the unique characteristics of different settings.

Universiti Utara Malaysia

This study integrated only two theories: TOE and DOI. Incorporating additional theories such as TPB, RBV, TAM, and UTAUT could provide better explanations and deeper insights into the factors influencing the adoption of BD in SMEs.

Lastly, we strongly encourage researchers and academics to investigate political instability as a moderating factor between TOE constructs and the IABD in SMEs. Given the unstable environment in Palestine, it is plausible that political instability can either strengthen or weaken these relationships. Understanding the impact of political instability on adopting BD is of utmost importance and requires immediate attention.

5.6 Conclusion

This study aimed to identify the factors influencing the IABD among Palestinian SMEs, with a particular focus on the moderating role of INNOV. Conducted within the unique socio-economic context of Palestine, the research utilised the TOE and DOI theory. Data were collected from 272 SMEs managers through a structured survey and analyzsd using PLS-SEM.

Key findings from the study indicate that several technological, organisational, and environmental factors significantly influence the IABD among Palestinian small and medium-sized enterprises. Specifically, technological factors such as RADV, COMP, CMPLX, TR, and OB were found to be crucial. These findings emphasize that SMEs are more likely to adopt BD if they perceive it as advantageous, compatible with their existing processes, not overly complex, and providing opportunities for experimentation and observable benefits.

Universiti Utara Malaysia

On the organisational front, TMS emerged as a critical factor, highlighting the importance of leadership commitment in fostering a conducive environment for BDA. EXSUPP and GOVS were also significant environmental factors, underscoring the need for external assistance and favorable policies to overcome resource constraints typically faced by SMEs. Interestingly, OR and COMPR did not significantly influence BDA intention, suggesting that while SMEs recognise the potential benefits of BD, their current infrastructure and the competitive environment may not be the primary drivers for adoption.

A notable contribution of this research is the identification of INNOV as a moderating factor. The findings reveal that INNOV strengthens the relationships between RADV,

OR, COMPR, and BDA intention. This underscores the critical role of an innovative culture in enhancing the perception and utilisation of BD technologies, regardless of other contextual factors.

This research holds significant theoretical and practical implications. Theoretically, it contributes to the existing body of knowledge by integrating the TOE framework and DOI theory in a developing country context. The findings suggest that these frameworks are useful for understanding BDA but could be enriched by incorporating additional theories such as the TPB, Institutional Theory, TAM and UTAUT. Practically, the study provides valuable insights for practitioners, including enhancing top management's awareness and support, strengthening partnerships with vendors, and advocating for supportive government policies.

The study utilised a rigorous methodology, collecting data from 272 SMEs managers in Palestine. A total of 533 questionnaires were administered both online and by hand, with 272 valid responses analysed after excluding the invalid ones. The analysis was conducted using PLS-SEM, ensuring a robust examination of the data. The survey data analysis showed that nine out of the eleven antecedents significantly impact BDA. Particularly, factors such as RADV, COMP, CMPLX, TR, OB, TMS, EXSUPP, and GOVS significantly affect BDA, while OR and COMPR were found to be insignificant.

Furthermore, given the unstable political environment in Palestine, future research should investigate political instability as a moderating factor. Understanding how political instability affects BDA could provide critical insights for both researchers and practitioners, particularly in developing countries facing similar challenges.

Universiti Utara Malaysia

In conclusion, this study provides a comprehensive analysis of the factors influencing the IABD among Palestinian SMEs. The findings highlight the significant roles of technological, organisational, and environmental factors, and the moderating influence of INNOV. By addressing the identified limitations and exploring the suggested future research directions, we can further our understanding of BDA and develop more effective strategies to support SMEs in leveraging BD for their growth and competitiveness. This research not only enriches academic discourse but also offers practical guidance for SMEs and policymakers aiming to harness the power of BD in challenging environments. It is anticipated that this study will stimulate further theoretical developments and inspire additional research endeavors, fostering a continuous scholarly discourse and encouraging future investigations, thereby enriching the academic landscape in this domain.

Universiti Utara Malaysia

REFERENCES

Abulehia, A. F. S., Khairudin, N., & Sharif, M. H. M. (2023). Factors influencing the intention to adopt big data in small medium enterprises. In M. Al-Emran, M. A. Al-Sharafi, & K. Shaalan (Eds.), *Lecture notes in networks and systems* (Vol. 550, pp. 137–149). Springer International Publishing. https://doi.org/10.1007/978-3-031-16865-9_12

Agarwal, A. (2016). Perspective: Materials informatics and big data: Realization of the "fourth paradigm" of science in materials science. *APL Materials, 4*(5). https://doi.org/10.1063/1.4946894

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research, 9*(2), 204–215. https://doi.org/10.1287/isre.9.2.204

Agrawal, K. P. (2015). Investigating the determinants of big data analytics (BDA) adoption in Asian emerging economies. *2015 Americas Conference on Information Systems (AMCIS 2015)*, 1–18. https://doi.org/10.5465/ambpp.2015.11290abstract

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-t

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice Hall.

Alaskar, T. H., Mezghani, K., & Alsadi, A. K. (2020). Examining the adoption of big data analytics in supply chain management under competitive pressure: Evidence from Saudi Arabia. *Journal of Decision Systems.* https://doi.org/10.1080/12460125.2020.1859714

Alfoqahaa, S. (2018). Critical success factors of small and medium-sized enterprises in Palestine. *Journal of Research in Marketing and Entrepreneurship, 20*(2), 170–188. https://doi.org/10.1108/JRME-05-2016-0014

Aligarh, F., Sutopo, B., & Widarjo, W. (2023). The antecedents of cloud computing adoption and its consequences for MSMEs' performance: A model based on the Technology-Organization-Environment (TOE) framework. *Cogent Business & Management, 10*(2), 2220190. https://doi.org/10.1080/23311975.2023.2220190

Al-Qirim, N. (2007). The adoption of e-commerce communications and applications technologies in small businesses in New Zealand. *Electronic Commerce Research and Applications, 6*(4), 462–473. https://doi.org/10.1016/j.elerap.2007.02.012

Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the North East of England: A multi-perspective framework. *Journal of*

Universiti Utara Malaysia

Enterprise Information Management, 26(3), 250–275. https://doi.org/10.1108/17410391311325225

Alshammari, A. S., Alshammari, H., & Alshammari, S. (2021). Factors associated with adherence to COVID-19 preventive measures among Saudi Arabians. *Cureus, 13*(4), e14623. https://doi.org/10.7759/cureus.14623

Ammar, A., & Ahmed, E. M. (2016). Factors influencing Sudanese microfinance intention to adopt mobile banking. *Cogent Business & Management, 3*(1), 1154257. https://doi.org/10.1080/23311975.2016.1154257

Amoah, J., Bruce, E., Shurong, Z., Bankuoru Egala, S., & Kwarteng, K. (2023). Social media adoption in SMEs sustainability: Evidence from an emerging economy. *Cogent Business & Management, 10*(1), 2183573. https://doi.org/10.1080/23311975.2023.2183573

Angwar, H., Gangwar, H., & Angwar, H. (2018). Understanding the determinants of big data adoption in India: An analysis of the manufacturing and services sectors. *Information Resources Management Journal, 31*(4), 1–22. https://doi.org/10.4018/IRMJ.2018100101

Armitage, C. J., & Conner, M. (2001). Efficacy of the Theory of Planned Behaviour: a meta-analytic review. *The British Journal of Social Psychology*, *40*(Pt 4), 471–499. https://doi.org/10.1348/014466601164939

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research, 14*, 396-402.

Asiaei, A., & Ab. Rahim, N. Z. (2019). A multifaceted framework for adoption of cloud computing in Malaysian SMEs. *Journal of Science and Technology Policy Management, 10*(3), 708–750. https://doi.org/10.1108/JSTPM-05-2018-0053

Awa, H. O., Ukoha, O., & Emecheta, B. C. (2016). Using T-O-E theoretical framework to study the adoption of ERP solution. *Cogent Business & Management, 3*(1), 1196571. https://doi.org/10.1080/23311975.2016.1196571

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2019). Big data adoption: State of the art and research challenges. *Information Processing & Management, 56*(6), 102095. https://doi.org/10.1016/j.ipm.2019.102095

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2021). A model for decision-makers' adoption of big data in the education sector. *Sustainability, 13*(24), 13995. https://doi.org/10.3390/su132413995

Baig, M. I., Yadegaridehkordi, E., & Nizam Bin Md Nasir, M. H. (2023). Influence of big data adoption on sustainable marketing and operation of SMEs: A hybrid approach of SEM–ANN. *Management Decision.* https://doi.org/10.1108/MD-06-2022-0778

Universiti Utara Malaysia

Baker, J. (2012). The technology–organization–environment framework. In Y. K. Dwivedi et al. (Eds.), *Information systems theory* (pp. 231–245). Springer.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Boonsiritomachai, W., McGrath, G. M., & Burgess, S. (2016). Exploring business intelligence and its depth of maturity in Thai SMEs. *Cogent Business & Management, 3*(1), 1220663. https://doi.org/10.1080/23311975.2016.1220663

Boubeta-Puig, J., Ortiz, G., & Medina-Bulo, I. (2014). A model-driven approach for facilitating user-friendly design of complex event patterns. *Expert Systems with Applications, 41*(2), 445–456. https://doi.org/10.1016/j.eswa.2013.07.070

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of cross-cultural psychology*, *1*(3), 185-216.

Brock, V., & Khan, H. U. (2017). Big data analytics: Does organizational factor matter for technology acceptance? *Journal of Big Data, 4*(1), 21. https://doi.org/10.1186/s40537-017-0081-8

Cavana, R. Y., Delahaye, B. L., & Sekaran, U. (2001). *Applied Business Research: Qualitative and Quantitative Methods*.

Cegielski, C.G., Jones-Farmer, L.A., Wu, Y., & Hazen, B.T. (2012). Adoption of cloud computing technologies in supply chains: An organizational information processing theory approach. *The International Journal of Logistics Management*, 23(2), 184-211.

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Thrassou, A. (2022). Impacts of big data analytics adoption on firm sustainability performance. *Qualitative Research in Financial Markets.* https://doi.org/10.1108/QRFM-01-2022-0005

Chaudhury, A., & Bharati, P. (2008). IT outsourcing adoption by small and medium enterprises: A diffusion of innovation approach. In *Proceedings of the Americas Conference on Information Systems (AMCIS).*

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly: Management Information Systems*, *36*(4), 1165–1188. https://doi.org/10.2307/41703503

Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile Networks and Applications, 19*(2), 171–209. https://doi.org/10.1007/s11036-013-0489-0

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems, 32*(4), 4–39. https://doi.org/10.1080/07421222.2015.1138364

Chin, W. W. (2010). How to write up and report PLS analyses. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares* (pp. 655–690). Springer. https://doi.org/10.1007/978-3-540-32827-8_29

Chuah, M. H., & Thurusamry, R. (2021). Challenges of big data adoption in Malaysia SMEs based on Lessig's modalities: A systematic review. *Cogent Business & Management*, *8*(1), 1968191. https://doi.org/10.1080/23311975.2021.1968191

Collis, J., & Hussey, R. (2003). *Business research: A practical guide for undergraduate and postgraduate students* (2nd ed.). Palgrave Macmillan.

Cooper, M., & Mell, P. (2012). Tackling big data. *NIST Computer Security Resource Center.*

Creswell, J. W. (2003) *Research Design: Qualitative, Quantitative and Mixed Methods Approach*, 2nd edition: Sage Publications, London.

Creswell, J. W. (2012). *Qualitative inquiry and research design: Choosing among five approaches* (3rd ed.). SAGE Publications.

Damanpour, F. (1991). Organizational innovation: A meta-analysis of effects of determinants and moderators. *Academy of Management Journal, 34*(3), 555–590.

Damanpour, F., & Schneider, M. (2006). Phases of the adoption of innovation in organizations: Effects of environment, organization and top managers[1]. *British Journal of Management*, *17*(3), 215–236. https://doi.org/10.1111/j.1467-8551.2006.00498.x

Davenport, T. H. (2014). Der Aufstieg von Analytics 3.0. In *Big data @ work* (pp. 193–201). Vahlen.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–340. https://doi.org/10.2307/249008

Dillman, D. A. (2000). *Mail and internet surveys: The tailored design method* (2nd ed.). John Wiley & Sons.

Dlamini, B. (2022). Factors influencing the use of management accounting practices among SMEs in emerging economies: A case of Zimbabwe. *The Journal of Accounting and Management, 12*(2).

Dlamini, Z. (2024). Influence of big data analytics on decision-making processes in financial firms in South Africa. *American Journal of Data, Information and Knowledge Management, 5*(1), 14–25. https://doi.org/10.47672/ajdikm.2350

Dogbe, C. S. K., Tian, H., Pomegbe, W. W. K., Sarsah, S. A., & Otoo, C. O. A. (2020). Effect of network embeddedness on innovation performance of small and medium-sized enterprises: The moderating role of innovation openness. *Journal*

Universiti Utara Malaysia

of Strategy and Management, 13(2), 181–197. https://doi.org/10.1108/JSMA-07-2019-0126

Domegan, C., & Fleming, D. (2007). *Marketing research in Ireland: Theory and practice* (3rd ed.). Gill & Macmillan.

Dremel, C., Herterich, M. M., Wulf, J., & vom Brocke, J. (2020). Actualizing big data analytics affordances: A revelatory case study. *Information & Management, 57*(1), 103121. https://doi.org/10.1016/j.im.2018.10.007

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers: A Journal of Research and Innovation*, *21*(3), 719–734. https://doi.org/10.1007/s10796-017-9774-y

Easterby-Smith, M., Thorpe, R., & Jackson, P. R. (2008). *Management research* (3rd ed.). SAGE Publications.

El-Haddadeh, R., Osmani, M., Hindi, N., & Fadlalla, A. (2021). Value creation for realising the sustainable development goals: Fostering organisational adoption of big data analytics. *Journal of Business Research*, *131*, 402–410. https://doi.org/10.1016/j.jbusres.2020.10.066

Elmashtawy, A., & Salaheldeen, M. (2023). Big data and business analytics: Evidence from Egypt. In M. Al-Emran, M. A. Al-Sharafi, & K. Shaalan (Eds.), *International conference on information systems and intelligent applications* (pp. 503–512). Springer International Publishing.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research.* Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Forootani, S., Abdolvand, N., & Harandi, S. R. (2022). Factors affecting the adoption of cloud-based CRM in small and medium enterprises. *International Journal of Services, Technology and Management, 28*(1–2), 120–140. https://doi.org/10.1504/IJSTM.2022.123509

Fowler, F. J., Jr. (2009). *Survey research methods* (4th ed.). SAGE Publications.

Gallego, J., Rubalcaba, L., & Hipp, C. (2013). Organizational innovation in small European firms: A multidimensional approach. *International Small Business Journal, 31*(5), 563–579. https://doi.org/10.1177/0266242611430100

Gangwar, H. (2018). Understanding the determinants of big data adoption in India: An analysis of the manufacturing and services sectors. *Information Resources Management Journal, 31*(4), 1–22. https://doi.org/10.4018/IRMJ.2018100101

Universiti Utara Malaysia

Ghaleb, E. A. A., Dominic, P. D. D., Fati, S. M., Muneer, A., & Ali, R. F. (2021). The assessment of big data adoption readiness with a technology–organization–environment framework: A perspective towards healthcare employees. *Sustainability, 13*(15), 8384. https://doi.org/10.3390/su13158379

Ghauri, P. N., & Grønhaug, K. (2005). *Research methods in business studies: A practical guide* (3rd ed.). Pearson Education.

Ghazi Naji, M., Fazidah Elias, N., Chun Lam, M., O. Abusamhadana, G. A., & Azlan Ahmad, N. (2022). Big data analytics adoption at higher education institutions in Iraq. *Journal of Theoretical and Applied Information Technology, 15*(9).

Ghobakhloo, M., Arias-Aranda, D., & Benitez-Amado, J. (2011). Adoption of e-commerce applications in SMEs. *Industrial Management + Data Systems*, *111*(8), 1238–1269. https://doi.org/10.1108/02635571111170785

Gorla, N., Somers, T. M., & Wong, B. (2010). Organizational impact of system quality, information quality, and service quality. *Journal of Strategic Information Systems*, *19*(3), 207–228. https://doi.org/10.1016/j.jsis.2010.05.001

Grant, D., & Yeo, B. (2018). A global perspective on tech investment, financing, and ICT on manufacturing and service industry performance. *International Journal of Information Management, 43*, 130–145. https://doi.org/10.1016/j.ijinfomgt.2018.06.007

Groves, R. M., Fowler, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2006). *Survey methodology* (2nd ed.). Wiley.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, 70*, 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004

Gupta, H., & Barua, M. K. (2016). Identifying enablers of technological innovation for Indian MSMEs using best–worst multi criteria decision making method. *Technological Forecasting and Social Change*, *107*, 69–79. https://doi.org/10.1016/j.techfore.2016.03.028

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Prentice Hall.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2013). Multivariate data analysis (7th ed.). Pearson Education Limited.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). A primer on partial least squares structural equation modeling (PLS-SEM). Sage Publications.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). Sage Publications.

Universiti Utara Malaysia

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*(3), 414–433. https://doi.org/10.1007/s11747-011-0261-6

Hassan, H. (2017). Organisational factors affecting cloud computing adoption in small and medium enterprises (SMEs) in service sector. *Procedia Computer Science, 121*, 976–981. https://doi.org/10.1016/j.procs.2017.11.126

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics & P. N. Ghauri (Eds.), *Advances in international marketing* (Vol. 20, pp. 277–319). Emerald Group Publishing. https://doi.org/10.1108/S1474-7979(2009)0000020014

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hult, G. T. M., Hurley, R. F., & Knight, G. A. (2004). Innovativeness: Its antecedents and impact on business performance. *Industrial Marketing Management, 33*(5), 429–438. https://doi.org/10.1016/j.indmarman.2003.08.015

Igbaria, M., Iivari, J., & Maragahh, H. (1995). Why do individuals use computer technology? A Finnish case study. *Information & Management, 29*(5), 227–238. https://doi.org/10.1016/0378-7206(95)00031-0

International Telecommunication Union. [ITU] (2017). *ICT development index 2017: Measuring the information society report.*. https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2017/MISR2017_Volume1.pdf

Iranmanesh, M., Lim, K. H., Foroughi, B., Hong, M. C., & Ghobakhloo, M. (2023). Determinants of intention to adopt big data and outsourcing among SMEs: Organisational and technological factors as moderators. *Management Decision, 61*(1), 201–222. https://doi.org/10.1108/MD-08-2021-1059

Ishtiaq, M. (2019). Book review Creswell, J. w. (2014). Research Design: Qualitative, quantitative and Mixed Methods Approaches (4th ed.). Thousand Oaks, CA: Sage. *English Language Teaching*, *12*(5), 40. https://doi.org/10.5539/elt.v12n5p40

Jang, W.-J., Kim, S.-S., Jung, S.-W., & Gim, G.-Y. (2019). A study on the factors affecting intention to introduce big data from smart factory perspective. In *Studies*

Universiti Utara Malaysia

in computational intelligence (Vol. 786, pp. 137–147). Springer International Publishing. https://doi.org/10.1007/978-3-319-96803-2_11

Ka, H.-K., & Kim, J.-S. (2014). An empirical study on the influencing factors for Big Data intended adoption: Focusing on the strategic value recognition and TOE framework. *Asia Pacific Journal of Information Systems, 24*(4), 443–472. https://doi.org/10.14329/apjis.2014.24.4.443

Kim, Y.-G., Lee, J., & Lee, T. (2018). Exploring determinants of semantic web technology adoption from IT professionals' perspective: Industry competition, organizational innovativeness, and data management capability. *International Journal of Data & Network Science, 2*(4), 277–290.

King, W., & He, J. (2005). External Validity in IS Survey Research. *Communications of the Association for Information Systems*, *16*, pp-pp. https://doi.org/10.17705/1CAIS.01645

Kirton, M. J. (2003). *Adaption–innovation: In the context of diversity and change.* Routledge.

Kline, R. B. (2005). *Principles and practice of structural equation modeling* (2nd ed.). Guilford Press.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607–610.

Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. *International Journal of Logistics Management, 29*(2), 676–703. https://doi.org/10.1108/IJLM-06-2017-0153

Le, H. M., Nguyen, T. T., & Hoang, T. C. (2020). Organizational culture, management accounting information, innovation capability and firm performance. *Cogent Business & Management, 7*(1), 1857594. https://doi.org/10.1080/23311975.2020.1857594

Lee, J. (2004). Discriminant analysis of technology adoption behavior: A case of internet technologies in small businesses. *Journal of Computer Information Systems, 44*(4), 57–66.

Lee, Y., Madnick, S. E., Wang, R. Y., Wang, F., & Zhang, H. (2014). A cubic framework for the Chief Data Officer: Succeeding in a world of big data. *MIS Quarterly Executive, 13*(1), 1–16.

Lin, A., & Chen, N.-C. (2012). Cloud computing as an innovation: Percepetion, attitude, and adoption. *International Journal of Information Management*, *32*(6), 533–540. https://doi.org/10.1016/j.ijinfomgt.2012.04.001

Lin, J., Luo, Z., & Luo, X. (2020). Understanding the roles of institutional pressures and organizational innovativeness in contextualized transformation toward e-

business: Evidence from agricultural firms. *International Journal of Information Management*, *51*(102025), 102025. https://doi.org/10.1016/j.ijinfomgt.2019.10.010

Lindawati, L., Leo Handoko, B., & Joyceline, I. (2023). Effect of technology, organization, environment and individual factors towards adoption intention of cloud-based accounting software in MSMEs. *Journal of Theoretical and Applied Information Technology, 15*(1).

Liu, L. (2013). 165. Liu defines big data as. *(Incomplete reference – please complete if used in thesis.)*

Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management + Data Systems*, *111*(7), 1006–1023. https://doi.org/10.1108/02635571111161262

Lu, Y., Quan, J., & Cao, X. (2009). The perceived attributes of Wi-Fi technology and the diffusion gap among university faculty members: A case study. *Communications of the Association for Information Systems, 24*(1), Article 5.

Lutfi, A., Almaiah, M. A., Alshira'h, A. F., Alshirah, M. H., Alsyouf, A., Al-Khasawneh, A. L., Alrawad, M., Al-Khasawneh, A., Saad, M., & Ali, R. (2022a). Antecedents of big data analytic adoption and impacts on performance: Contingent effect. *Sustainability, 14*(23), 15516. https://doi.org/10.3390/su142315516

Lutfi, A., Alsyouf, A., Almaiah, M. A., Alrawad, M., Abdo, A. A. K., Al-Khasawneh, A. L., Ibrahim, N., & Saad, M. (2022b). Factors influencing the adoption of big data analytics in the digital transformation era: Case study of Jordanian SMEs. *Sustainability, 14*(3), 1802. https://doi.org/10.3390/su14031802

Maduku, D. K., Mpinganjira, M., & Duh, H. (2016). Understanding mobile marketing adoption intention by South African SMEs: A multi-perspective framework. *International Journal of Information Management*, *36*(5), 711–723. https://doi.org/10.1016/j.ijinfomgt.2016.04.018

Mahesh, D. D., Vijayapala, S., & Dasanayaka, S. W. S. B. (2018). Factors affecting the intention to adopt big data technology: A study based on financial services industry of Sri Lanka. *MERCon 2018 – 4th International Multidisciplinary Moratuwa Engineering Research Conference* (pp. 420–425). https://doi.org/10.1109/MERCon.2018.8421917

Malik, M. S., Chadhar, M., & Chetty, M. (2021). Factors affecting the organizational adoption of blockchain technology: An Australian perspective. *Proceedings of the 54th Hawaii International Conference on System Sciences*.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). *Big data: The next frontier for innovation, competition, and productivity.* McKinsey Global Institute.

Universiti Utara Malaysia

Marcati, A., Guido, G., & Peluso, A. M. (2008). The role of SME entrepreneurs' innovativeness and personality in the adoption of innovations. *Research Policy, 37*(9), 1579–1590. https://doi.org/10.1016/j.respol.2008.06.004

Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2023). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems, 122*(6), 1463–1488. https://doi.org/10.1108/IMDS-11-2021-0695

Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020a). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, *54*, 102190. https://doi.org/10.1016/j.ijinfomgt.2020.102190

Maroufkhani, P., Wan Ismail, W. K., & Ghobakhloo, M. (2020b). Big data analytics adoption model for small and medium enterprises. *Journal of Science and Technology Policy Management*, *11*(2), 171–201. https://doi.org/10.1108/JSTPM-02-2020-0018

McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10), 60–66, 68, 128.

Mneney, J., Van Belle, J.-P., & Belle, J. Van. (2016). Big data capabilities and readiness of South African retail organisations. *Proceedings of the 2016 6th International Conference – Cloud System and Big Data Engineering (Confluence 2016)* (pp. 279–286). https://doi.org/10.1109/CONFLUENCE.2016.7508129

Mohd Sharif, M. H., Troshani, I., & Davidson, R. (2016). Determinants of social media impact in local government. *Journal of Organizational and End User Computing, 28*(3), 82–103. https://doi.org/10.4018/JOEUC.2016070106

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Nagaraj, K., Sharvani, G. S., & Sridhar, A. (2018). Emerging trend of big data analytics in bioinformatics: A literature review. *International Journal of Bioinformatics Research and Applications, 14*(1–2), 144–160. https://doi.org/10.1504/IJBRA.2018.089175

Nam, D. W., Kang, D., & Kim, S. H. (2015). Process of big data analysis adoption: Defining big data as a new IS innovation and examining factors affecting the process. *Proceedings of the 48th Hawaii International Conference on System Sciences* (pp. 4792–4801). https://doi.org/10.1109/HICSS.2015.569

Nasrollahi, M., Ramezani, J., & Sadraei, M. (2021). The impact of big data adoption on SMEs' performance. *Big Data and Cognitive Computing, 5*(4), 68. https://doi.org/10.3390/bdcc5040068

Neuman, W. L. (2005). *Social research methods: Quantitative and qualitative approaches* (6th ed.). Allyn & Bacon.

Nguyen, G. T. T., Liaw, S.-Y., & Duong, X.-L. (2022). Readiness of SMEs for adopt big data: An empirical study in Vietnam. *International Journal of Computing and Digital Systems, 12*(1), 509–521. https://doi.org/10.12785/IJCDS/120141

Organisation for Economic Co-operation and Development [OECD] (2021), The Digital Transformation of SMEs, OECD Studies on SMEs and Entrepreneurship, OECD Publishing, Paris, https://doi.org/10.1787/bdb9256a-en.

Oliveira, T., & Martins, M. F. (2010). Understanding e-business adoption across industries in European countries. *Industrial Management & Data Systems, 110*(9), 1337–1354. https://doi.org/10.1108/02635571011087428

Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management, 51*(5), 497–510. https://doi.org/10.1016/j.im.2014.03.006

Palestinian Council of Ministers. (2011). *Decision of the Palestinian Council of Ministers No. (08/74/13/M.W/S.F) for the year 2011*. Ramallah, Palestine.

Park, J. H., & Kim, Y. B. (2021). Factors activating big data adoption by Korean firms. *Journal of Computer Information Systems, 61*(3), 285–293. https://doi.org/10.1080/08874417.2019.1631133

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned Behavior1. *MIS Quarterly: Management Information Systems*, *30*(1), 115–143. https://doi.org/10.2307/25148720

Palestinian Central Bureau of Statistics [PCBS]. (2022). *ICT business survey 2021.* Palestinian Central Bureau of Statistics. http://www.pcbs.gov.ps

Podsakoff, P. M., & Organ, D. W. (1986). *Self-reports in organizational research: Problems and prospects*. Journal of Management, 12(4), 531–544. https://doi.org/10.1177/014920638601200408

Premkumar, G., & Roberts, M. (1999). Adoption of new information technologies in rural small businesses. *Omega, 27*(4), 467–484. https://doi.org/10.1016/S0305-0483(98)00071-1

Priyadarshinee, P., Raut, R. D., Jha, M. K., & Kamble, S. S. (2017). A cloud computing adoption in Indian SMEs: Scale development and validation approach. *The Journal of High Technology Management Research*, *28*(2), 221–245. https://doi.org/10.1016/j.hitech.2017.10.010

Pu, G., Li, Y., & Bai, J. (2018). The effect of big data analytics on firms' sustainable competitive advantage of quality: A theory framework. *ACM International*

Conference Proceeding Series (pp. 33–37). https://doi.org/10.1145/3277139.3277144

Rajabion, L. (2018). Application and adoption of big data technologies in SMEs. In *2018 International Conference on Computational Science and Computational Intelligence (CSCI 2018)* (pp. 1133–1135). https://doi.org/10.1109/CSCI46756.2018.00219

Ramdani, B., Chevers, D., & Williams, D. A. (2013). SMEs' adoption of enterprise applications: A technology–organisation–environment model. *Journal of Small Business and Enterprise Development, 20*(4), 735–753. https://doi.org/10.1108/JSBED-12-2011-0035

Ramdani, B., & Kawalek, P. (2008). SMEs & IS innovations adoption: A review & assessment of previous research. *Academia. Revista Latinoamericana de Administración, 39*, 47–70.

Ramdani, B., Kawalek, P., & Lorenzo, O. (2009). Predicting SMEs' adoption of enterprise systems. *Journal of Enterprise Information Management*, *22*(1/2), 10–24. https://doi.org/10.1108/17410390910922796

Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). Free Press.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Saetang, W., Tangwannawit, S., & Jensuttiwetchakul, T. (2020). The effect of technology–organization–environment on adoption decision of big data technology in Thailand. *International Journal of Electrical and Computer Engineering, 10*(6), 6412–6422. https://doi.org/10.11591/ijece.v10i6.pp6412-6422

Salisu, I., Bin Mohd Sappri, M., & Bin Omar, M. F. (2021). The adoption of business intelligence systems in small and medium enterprises in the healthcare sector: A systematic literature review. *Cogent Business & Management*, *8*(1), 1935663. https://doi.org/10.1080/23311975.2021.1935663

Salkind, N. J. (1997). Gender and Age Differences in Preference for Works of Art Gender and Age Differences in Preference for Works of. *Studies in Art Education*, *38*(4), 246–256.

Salleh, K. A., & Janczewski, L. (2018). An implementation of sec-TOE framework: Identifying security determinants of big data solutions adoption. In *Proceedings of the 22nd Pacific Asia Conference on Information Systems (PACIS 2018).*

Sam, K. M., & Chatwin, C. R. (2019). Understanding adoption of big data analytics in China: From organizational users' perspective. In *IEEE International Conference on Industrial Engineering and Engineering Management* (pp. 507–510). https://doi.org/10.1109/IEEM.2018.8607652

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2009). *Research methods for business students* (5th ed.). Pearson Education.

Schüll, A., Maslan, N., & INSTICC. (2018). On the adoption of big data analytics: Interdependencies of contextual factors. In *ICEIS 2018 – Proceedings of the 20th International Conference on Enterprise Information Systems* (Vol. 1, pp. 425–431). https://doi.org/10.5220/0006759904250431

Sekaran, U. (2003). *Research methods for business: A skill-building approach* (4th ed.). John Wiley & Sons.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). John Wiley & Sons.

Shafique, I., Ahmad, B., & Kalyar, M. N. (2019). How ethical leadership influences creativity and organizational innovation: Examining the underlying mechanisms. *European Journal of Innovation Management, 23*(1), 114–133. https://doi.org/10.1108/EJIM-12-2018-0269

Shahadat, M. M. H., Nekmahmud, M., Ebrahimi, P., & Fekete-Farkas, M. (2023). Digital technology adoption in SMEs: What technological, environmental and organizational factors influence SMEs' ICT adoption in emerging countries? *Global Business Review.* https://doi.org/10.1177/09721509221137199

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Khan, I. (2021). Environmental air pollution management system: Predicting user adoption behavior of big data analytics. *Technology in Society*, *64*(101473), 101473. https://doi.org/10.1016/j.techsoc.2020.101473

Sharma, M., Gupta, R., Sehrawat, R., Jain, K., & Dhir, A. (2023). The assessment of factors influencing big data adoption and firm performance: Evidence from an emerging economy. *Enterprise Information Systems.* https://doi.org/10.1080/17517575.2023.2218160

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. *The Journal of Consumer Research*, *15*(3), 325. https://doi.org/10.1086/209170

Shin, D.-H. (2016). The big data analytic capability and adoption factors in Korean firms: An integrative framework. *Journal of Open Innovation: Technology, Market, and Complexity, 2*(14), 1–13.

Singh, R., Sharma, P., Foropon, C., & Belal, H. M. (2022). The role of big data and predictive analytics in employee retention: A resource-based view. *International Journal of Manpower, 43*(2), 411–447. https://doi.org/10.1108/IJM-03-2021-0197

Universiti Utara Malaysia

Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2018). Understanding the factors affecting the organizational adoption of big data. *Journal of Computer Information Systems, 58*(3), 193–203. https://doi.org/10.1080/08874417.2016.1222891

Sun, S., Hall, D. J., & Cegielski, C. G. (2020). Organizational intention to adopt big data in the B2B context: An integrated view. *Industrial Marketing Management, 86*, 109–121. https://doi.org/10.1016/j.indmarman.2019.09.003

Tabachnick, B. G., & Fidell, L. S. (2001). *Using multivariate statistics* (4th ed.). Allyn and Bacon.

Tamin, M., & Adis, A. A. A. (2022). The impact of TOE framework on e-commerce advantage among small medium enterprise (SMEs) digital channel in Malaysia. *Journal of Distribution Science, 20*(8), 33–46. https://doi.org/10.15722/jds.20.08.202208.33

Taxman, F. S., Henderson, C., Young, D., & Farrell, J. (2014). The impact of training interventions on organizational readiness to support innovations in juvenile justice offices. *Administration and Policy in Mental Health*, *41*(2), 177–188. https://doi.org/10.1007/s10488-012-0445-5

Thong, J. Y. L. (1999). An integrated model of information systems adoption in small businesses. *Journal of Management Information Systems, 15*(4), 187–214. https://doi.org/10.1080/07421222.1999.11518227

Thong, J. Y. L., Yap, C.-S., & Raman, K. S. (1996). Top management support, external expertise and information systems implementation in small businesses. *Information Systems Research, 7*(2), 248–267. https://doi.org/10.1287/isre.7.2.248

Tien, E. L., Ali, N. M., Miskon, S., Ahmad, N., & Abdullah, N. S. (2020). Big data analytics adoption model for Malaysian SMEs. In *Advances in intelligent systems and computing* (Vol. 1073, pp. 45–57). https://doi.org/10.1007/978-3-030-33582-3_5

Tornatzky, L. G., & Fleischer, M. (1990). *Processes of technological innovation.* Lexington Books.

Trisnadewi, A. A. A. E., Sr, Purnami, A. A. S., Sr, Amlayasa, A. A. B., Sr, & Putra, I. G. L., Sr. (2024). Determinants of Big Data Analytics adoption by small and medium industries (SMEs) in the perspective of the technological-organizational-environmental (TOE) model in Bali. *International Journal of Science and Management Studies (IJSMS)*, 109–118. https://doi.org/10.51386/25815946/ijsms-v7i5p108

Truong, N. X. (2022). Factors affecting big data adoption: An empirical study in small and medium enterprises in Vietnam. *International Journal of Asian Business and Information Management, 13*(1), 1–18. https://doi.org/10.4018/IJABIM.315825

Universiti Utara Malaysia

Tsai, M.-C., Lee, W., & Wu, H.-C. (2010). Determinants of RFID adoption intention: Evidence from Taiwanese retail chains. *Information & Management*, *47*(5–6), 255–261. https://doi.org/10.1016/j.im.2010.05.001

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of Technology1. *MIS Quarterly: Management Information Systems*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Verma, S. (2017). The adoption of Big Data Services by Manufacturing firms: An empirical investigation in India. *Journal of Information Systems and Technology Management*, *14*(1), 39–68. https://doi.org/10.4301/s1807-17752017000100003

Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of big data analytics in emerging economy: A qualitative approach for Indian firms. *Journal of Enterprise Information Management, 30*(3), 354–382. https://doi.org/10.1108/JEIM-10-2015-0099

Verma, S., & Chaurasia, S. (2019). Understanding the determinants of big data analytics adoption. *Information Resources Management Journal, 32*(3), 1–26. https://doi.org/10.4018/IRMJ.2019070101

Wahab, S. N., & Olugu, E. U. (2018). Big data analytics adoption in the Malaysian warehousing industry. In *Proceedings of the 32nd International Business Information Management Association Conference.*

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change, 126*, 3–13. https://doi.org/10.1016/j.techfore.2015.12.019

Wang, Y.-M., Wang, Y.-S., & Yang, Y.-F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting and Social Change*, *77*(5), 803–815. https://doi.org/10.1016/j.techfore.2010.03.006

Wejnert, B. (2002). Integrating models of diffusion of innovations: A conceptual framework. *Annual Review of Sociology*, *28*(1), 297–326. https://doi.org/10.1146/annurev.soc.28.110601.141051

Xu, W., Ou, P., & Fan, W. (2017). Antecedents of ERP assimilation and its impact on ERP value: A TOE-based model and empirical test. *Information Systems Frontiers, 19*(1), 13–30. https://doi.org/10.1007/s10796-015-9583-0

Yadegaridehkordi, E., Hourmand, M., Nilashi, M., Shuib, L., Ahani, A., & Ibrahim, O. (2018). Influence of big data adoption on manufacturing companies' performance: An integrated DEMATEL–ANFIS approach. *Technological Forecasting and Social Change, 137*, 199–210. https://doi.org/10.1016/j.techfore.2018.07.043

Yadegaridehkordi, E., Nilashi, M., Shuib, L., Hairul Nizam Bin Md Nasir, M., Asadi, S., Samad, S., & Awang, N. F. (2020). The impact of big data on firm performance in hotel industry. *Electronic Commerce Research and Applications, 40*, 100921. https://doi.org/10.1016/j.elerap.2019.100921

Yeşil, S., Koska, A., & Büyükbeşe, T. (2013). Knowledge sharing process, innovation capability and innovation performance: An empirical study. *Procedia – Social and Behavioral Sciences, 75*, 217–225. https://doi.org/10.1016/j.sbspro.2013.04.025

Yoon, T. E., & George, J. F. (2013). Why aren't organizations adopting virtual worlds? *Computers in Human Behavior*, *29*(3), 772–790. https://doi.org/10.1016/j.chb.2012.12.003

Zhu, K., Dong, S., Xu, S. X., & Kraemer, K. L. (2006). Innovation diffusion in global contexts: Determinants of post-adoption digital transformation of European companies. *European Journal of Information Systems, 15*(6), 601–616. https://doi.org/10.1057/palgrave.ejis.3000650

Zikmund, W. G. (2000). *Business research methods* (6th ed.). Dryden Press.

Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2013). *Business research methods* (9th ed.). Cengage Learning.

Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2013). *Business research methods* (8th ed.). South-Western, Cengage Learning.

Zomaya, A. Y., & Sakr, S. (Eds.). (2017). *Handbook of big data technologies.* Springer.

Universiti Utara Malaysia

APPENDIX

APPENDIX A

DESCREPTIVE STATISTICS

Descriptive statistic for related items to technological factors of the intention to adopt big data.

	Item	Mean	SD
RADV1	Big Data improves the quality of work	3.29	1.241
RADV2	Big Data makes work more efficient	3.25	1.220
RADV3	Big Data lowers costs	3.32	1.155
RADV4	Big Data improves customer service	3.38	1.181
RADV5	Big Data attracts new sales to new customers or new markets	3.30	1.202
RADV6	Big Data adoption identifies new product/service opportunities	3.17	1.222
COMP1	Big Data provides flexible architecture, which is compatible to various analytical tasks.	3.34	1.108
COMP2	Big Data architecture are compatible to schemas used for storing data.	3.36	1.160
COMP3	Big Data is compatible with existing technological architecture.	3.31	1.049
COMP4	It is easy to synchronize external data with organisation's internal data.	3.38	1.079
CMPLX1	It is difficult to normalize huge amount of unstructured data from multiple sources to make it compatible with structured data.	3.20	1.158
CMPLX2	The interpretation of big data analysis results to extract actionable knowledge is difficult.	3.14	1.111
CMPLX3	It is difficult to integrate data, across multiple incompatible databases among various stakeholders	3.04	1.124
CMPLX4	It is difficult to integrate data across silos.	3.10	1.165
TR1	Our company could access to a free trial before deciding to adopt Big Data Analytics	3.58	0.666
TR2	Our company could try several Big Data Analytics applications before deciding and try out Big Data Analytics software packages on a s sufficiently large scale	3.53	0.654
TR3	Our company is allowed to use Big Data Analytics on a trial basis long enough to see its true capabilities	3.53	0.619
TR4	It is easy to get out after testing a Big Data Analytics package	3.44	0.586
TR5	The start-up cost for using Big Data Analytics is low	3.51	0.563
OB1	Many competitors or business partners in the market have started using Big Data.	3.39	1.154
OB2	Using Big Data helps our company to connect with both domestic and international business partners.	3.25	1.131
OB3	There are many computers that people in the company can access to use Big Data.	3.39	1.243
OB4	Big Data shows improved results over doing business by traditional way.	3.28	1.183
OB5	Big Data shows improved results over doing business by traditional way.	3.29	1.146

Universiti Utara Malaysia

Descriptive statistic for related items to organisational factors of the intention to adopt big data.

	Item	Mean	SD
TMS1	Top management would provide resources necessary for the adoption of big data.	3.50	1.193
TMS2	Top management would provide necessary support for the adoption of big data.	3.44	1.128
TMS3	Top management would support the use of big data.	3.45	1.139
TMS4	Top managers would be enthusiastic about adopting big data.	3.42	1.140
OR1	lacking capital/financial resources has prevented our company from fully exploit Big Data.	3.26	1.150
OR2	lacking IT infrastructure has prevented our company from exploiting Big Data.	3.22	1.139
OR3	lacking analytics capability prevent the business fully exploit Big Data.	3.23	1.147
OR4	Lacking skilled resources prevent the business fully exploit Big Data.	3.33	1.104

Descriptive statistic for related items to environmental factors of the intention to adopt big data.

	Item	Mean	SD
COMPR1	Our choice to adopt Big Data Analytics would be strongly influenced by what competitors in the industry are doing	3.39	1.173
COMPR2	Our firm is under pressure from competitors to adopt Big Data Analytics	3.38	1.178
COMPR3	Our firm would adopt Big Data Analytics in response to what competitors are doing	3.35	1.137
EXSUPP1	Community agencies/vendors can provide required training for Big Data adoption.	3.33	0.968
EXSUPP2	Community agencies/vendors can provide effective technical support for Big Data adoption.	3.44	0.985
EXSUPP3	Vendors actively market Big Data adoption.	3.39	0.974
GOVS1	The governmental policies encourage us to adopt new information technology (e.g., big data).	3.35	1.136
GOVS2	The government provides incentives for using big data analytics in government procurements and contracts such as offering technical support, training, and funding for big data.	3.33	1.100
GOVS3	There are some business laws to deal with the security and privacy concerns over the Big Data technology	3.38	1.123

Descriptive statistic for related items to innovation of organisations.

	Item	Mean	SD
INNOV1	Our company frequently tries out new ideas.	3.42	1.111
INNOV2	Our company seeks out new ways to do things.	3.37	1.099
INNOV3	Our company is creative in its methods of operation.	3.40	1.061
INNOV4	Our company is often the first to market with new products and services.	3.39	1.094
INNOV5	Innovation in our company is seen as a valuable opportunity and is actively supported.	3.40	1.167
INNOV6	Our new product introduction has increased over the last 5 years.	3.44	1.125

Universiti Utara Malaysia

Descriptive statistic for related items to the intention to adopt big data.

	Item	Mean	SD
IABD1	Our firm intends to adopt big data.	3.37	1.279
IABD2	Our firm intends to start using big data regularly in the future.	3.45	1.205
IABD3	Our firm would highly recommend big data for other enterprises to adopt.	3.53	1.174
IABD4	Our firm intend to use big data in the next few months.	3.57	1.260

Universiti Utara Malaysia

APPENDIX B

NORMALITY TEST

	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
RADV1	272	-0.361	0.148	-0.897	0.294
RADV2	272	-0.128	0.148	-1.006	0.294
RADV3	272	-0.295	0.148	-0.859	0.294
RADV4	272	-0.201	0.148	-1.022	0.294
RADV5	272	-0.316	0.148	-0.916	0.294
RADV6	272	-0.347	0.148	-0.941	0.294
COMP1	272	-0.225	0.148	-0.715	0.294
COMP2	272	-0.284	0.148	-0.708	0.294
COMP3	272	-0.336	0.148	-0.515	0.294
COMP4	272	-0.347	0.148	-0.614	0.294
CMPLX1	272	-0.121	0.148	-1.010	0.294
CMPLX2	272	-0.149	0.148	-0.730	0.294
CMPLX3	272	-0.096	0.148	-0.886	0.294
CMPLX4	272	-0.258	0.148	-0.778	0.294
TR1	272	-0.124	0.148	-0.147	0.294
TR2	272	-0.509	0.148	0.376	0.294
TR3	272	0.345	0.148	-0.369	0.294
TR4	272	0.397	0.148	-0.310	0.294
TR5	272	0.518	0.148	-0.753	0.294
OB1	272	-0.251	0.148	-0.808	0.294
OB2	272	-0.219	0.148	-0.689	0.294
OB3	272	-0.390	0.148	-0.849	0.294
OB4	272	-0.362	0.148	-0.761	0.294
OB5	272	-0.350	0.148	-0.827	0.294
TMS1	272	-0.553	0.148	-0.579	0.294
TMS2	272	-0.504	0.148	-0.502	0.294
TMS3	272	-0.516	0.148	-0.477	0.294
TMS4	272	-0.264	0.148	-0.759	0.294
OR1	272	-0.260	0.148	-0.695	0.294
OR2	272	-0.253	0.148	-0.770	0.294
OR3	272	-0.197	0.148	-0.796	0.294
OR4	272	-0.320	0.148	-0.582	0.294
COMPR1	272	-0.216	0.148	-0.978	0.294
COMPR2	272	-0.220	0.148	-0.778	0.294
COMPR3	272	-0.270	0.148	-0.799	0.294

Universiti Utara Malaysia

EXSUPP1	272	-0.032	0.148	-0.476	0.294
EXSUPP2	272	-0.045	0.148	-0.652	0.294
EXSUPP3	272	-0.229	0.148	-0.417	0.294
GOVS1	272	-0.413	0.148	-0.663	0.294
GOVS2	272	-0.325	0.148	-0.571	0.294
GOVS3	272	-0.410	0.148	-0.518	0.294
INNOV1	272	-0.202	0.148	-1.064	0.294
INNOV2	272	-0.096	0.148	-0.984	0.294
INNOV3	272	-0.101	0.148	-0.938	0.294
INNOV4	272	-0.149	0.148	-0.966	0.294
INNOV5	272	-0.072	0.148	-1.136	0.294
INNOV6	272	-0.197	0.148	-1.032	0.294
IABD1	272	-0.446	0.148	-0.935	0.294
IABD2	272	-0.659	0.148	-0.499	0.294
IABD3	272	-0.578	0.148	-0.483	0.294
IABD4	272	-0.702	0.148	-0.498	0.294
Valid N (listwise)	272				

Universiti Utara Malaysia

APPENDIX C

Correlation Matrix

	RADV	COMP	CMPLX	TR	OB	TMS	OR	COMPR	EXSUPP	GOVS	INNOV
RADV	1	.474**	.473**	-0.008	.457**	-.422**	.491**	.527**	0.019	.461**	.150*
COMP	.474**	1	.583**	0.085	.572**	-.459**	.617**	.569**	0.062	.535**	.180**
CMPLX	.473**	.583**	1	0.083	.574**	-.422**	.620**	.673**	.231**	.572**	.176**
TR	-0.008	0.085	0.083	1	0.063	0.006	0.047	0.070	-0.012	0.031	-0.118
OB	.457**	.572**	.574**	0.063	1	-.554**	.590**	.575**	-0.015	.534**	.259**
TMS	-.422**	-.459**	-.422**	0.006	-.554**	1	-.516**	-.397**	0.055	-.397**	-.244**
OR	.491**	.617**	.620**	0.047	.590**	-.516**	1	.625**	0.095	.578**	.210**
COMPR	.527**	.569**	.673**	0.070	.575**	-.397**	.625**	1	.120*	.545**	.189**
EXSUPP	0.019	0.062	.231**	-0.012	-0.015	0.055	0.095	.120*	1	0.101	-0.011
GOVS	.461**	.535**	.572**	0.031	.534**	-.397**	.578**	.545**	0.101	1	.183**
INNOV	.150*	.180**	.176**	-0.118	.259**	-.244**	.210**	.189**	-0.011	.183**	1
IABD	.645**	.708**	.742**	0.075	.727**	-.639**	.786**	.740**	0.021	.685**	.297**
N	272	272	272	272	272	272	272	272	272	272	272

**. Correlation is significant at the 0.01 level (2-tailed).

Universiti Utara Malaysia

APPENDIX D





No. Series

Dear Sir/Madam,

FACTORS INFLUENCING THE INTENTION TO ADOPT BIG DATA AMONG SMEs IN PALESTINE

I am a PhD student (ID: 903747) at School of Accountancy, the College of Business, Universiti Utara Malaysia. As part of my study toward a PhD, I am conducting a survey to determine the factors that influencing the intention to adopt big data among SMES in Palestine.

I hope that you will assist me in ensuring the success of this study by completing the enclosed questionnaire. If you wish, you might want to pass this survey to a more appropriate person in the organisation. This research is purely an academic study. I assure you that all the information provided will remain anonymous and strictly confidential. The results will only be presented in aggregate form and no single firm's result will be identified.

Universiti Utara Malaysia

Your prompt response would be very much appreciated. Should you need any further clarification, I would be pleased to assist you, or you may also contact my supervisor as shown below.

Thank you in advance for your kind cooperation.

Sincerely,	Supervised by:	Supervised by:
Ahmed F. S. Abulehia.	Dr. Norhaiza bt. Khairudin.	Dr. Mohd Hisham Mohd Sharif.
ahmed.abulehia@gmail.com	norhaiza@uum.edu.my	hisham79@uum.edu.my
Tel: +970599223860	Tel: 04-9287298	Tel: 04-9287277

***SECTION 1*: ABOUT YOU AND YOUR COMPANY**

Please respond to the following items by checking (✔) the appropriate box or completing the space provided.

Does your company intend to adopt big data?

□ Yes □ No

If your answer yes, please proceed with the questionnaire.

1. **Our firm plans using big data in the next?**

□ Three months □ Six months Nine months

□ One year □ Others (please specify _____)

2. **Location of business in Palestine – Gaza Strip**

□ Gaza district □ Khan Younis district □ Northern district

□ Middle district □ Rafah district

3. **In which Industry does your company operate?**

□ Manufacturing □ Services □ Merchandizing

□ Construction □ Other (please specify: _____)

4. **Please estimate the number of company's equivalent full-time employees.**

□ 1 – 4 □ 5 – 19 □ 20 – 49

□ Above 50

5. **Please estimate your company's 2020 annual sales/ turnover.**

□ ≤ $ 20,000 □ $ 20,001– $ 200,000

□ $ 200,00 1– $ 500,000 □ Above $ 500,000

6. **Please estimate your company's 2020 Registered capital.**

□ ≤ $ 5000 □ $ 5001– $ 50,000

□ $ 50,001 – $ 100,000 □ Above $ 100,000

7. **Please indicate the company's age.**

□ Less than 5 years □ 5 – 10 years □ 11 – 20 years

□ 21 – 30 years □ 31 – 40 years □ More than 40 years

8. **How many years have you been working in this company?**

□ Less than 5 years □ 5 – 10 years □ 11 – 20 years

□ 21 – 30 years □ More than 30 years

9. **Your highest academic level qualification is**

□ Diploma □ Bachelor degree □ Master / PhD

□ Professional qualification □ Others (please specify _____)

10. **Which of the following category best explains your current position?**

□ Top management □ Middle management □ First level management

□ Other (please specify:_____)

11. How long have you been holding the managerial position in this company?

□ Below 5 years □ 5 to 10 years □ 11 to 20 years □ Above 20 years

Please note that in all the following sections of the survey, the responses should be interpreted as follows: (Strongly disagree = 1, Disagree = 2, Neither agree nor disagree = 3, Agree = 4, Strongly agree = 5)

SECTION 2: Intention to Adopt Big Data

Please indicate to what extent the following statements describe the intention to adopt big data in your company.

	Intention to Adopt Big Data	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	Our firm intends to adopt big data.	1	2	3	4	5
2.	Our firm intends to start using big data regularly in the future.	1	2	3	4	5
3.	Our firm would highly recommend big data for other enterprises to adopt.	1	2	3	4	5
4.	Our firm intend to use big data in the next few months.	1	2	3	4	5

SECTION 3: Technological Factors

Please indicate to what extent the following statements describe the technological factors when adopting big data in your company.

Universiti Utara Malaysia

1.	**Relative advantage**	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	Big Data improves the quality of work	1	2	3	4	5
2.	Big Data makes work more efficient	1	2	3	4	5
3.	Big Data lowers costs	1	2	3	4	5
4.	Big Data improves customer service	1	2	3	4	5
5	Big Data attracts new sales to new customers or new markets	1	2	3	4	5
6.	Big Data adoption identifies new product/service opportunities	1	2	3	4	5

Universiti Utara Malaysia

	Compatibility	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	Big Data provides flexible architecture, which is compatible to various analytical tasks.	1	2	3	4	5
2.	Big Data architecture are compatible to schemas used for storing data.	1	2	3	4	5
3.	Big Data is compatible with existing technological architecture.	1	2	3	4	5
4.	It is easy to synchronize external data with organisation's internal data.	1	2	3	4	5

	Complexity	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	It is difficult to normalize huge amount of unstructured data from multiple sources to make it compatible with structured data.	1	2	3	4	5
2.	The interpretation of big data analysis results to extract actionable knowledge is difficult.	1	2	3	4	5
3.	It is difficult to integrate data, across multiple incompatible databases among various stakeholders	1	2	3	4	5
4.	It is difficult to integrate data across silos.	1	2	3	4	5

Universiti Utara Malaysia

	Trialability	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	Our company could access to a free trial before making a decision to adopt Big Data Analytics	1	2	3	4	5
2.	Our company has the opportunity to try a number of Big Data Analytics applications before making a decision and try out Big Data Analytics software packages on a s sufficiently large scale	1	2	3	4	5
3.	Our company is allowed to use Big Data Analytics on a trial basis long enough to see its true capabilities	1	2	3	4	5

4.	It is easy to get out after testing a Big Data Analytics package					
5.	The start-up cost for using Big Data Analytics is low	1	2	3	4	5

	Observability	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	Many competitors or business partners in the market have started using Big Data.	1	2	3	4	5
2.	Using Big Data helps our company to connect with both domestic and international business partners.	1	2	3	4	5
3.	There are many computers that people in the company can access to use Big Data.	1	2	3	4	5
4.	Big Data shows improved results over doing business by traditional way.	1	2	3	4	5

Universiti Utara Malaysia

SECTION 4: **Organizational Factors**

Please indicate to what extent the following statements describe the organisational factors when adopting big data in your company.

	Top Management Support	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	Top management would provide resources necessary for the adoption of big data.	1	2	3	4	5
2.	Top management would provide necessary support for the adoption of big data.	1	2	3	4	5

3.	Top management would support the use of big data.	1	2	3	4	5
4.	Top managers would be enthusiastic about adopting big data.	1	2	3	4	5

	Organizational Readiness	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1.	lacking capital/financial resources has prevented our company from fully exploit Big Data.	1	2	3	4	5
2.	lacking IT infrastructure has prevented our company from exploiting Big Data.	1	2	3	4	5
3.	lacking analytics capability prevent the business fully exploit Big Data.	1	2	3	4	5
4.	Lacking skilled resources prevent the business fully exploit Big Data.	1	2	3	4	5

Universiti Utara Malaysia

SECTION 5: **Environmental Factors**

Please indicate to what extent the following statements describe the environmental factors when adopting big data in your company.

	Competitive pressure	Strongly disagree	Disagree	Neither agree nor	Agree	Strongly agree
1.	Our choice to adopt Big Data Analytics would be strongly influenced by what competitors in the industry are doing	1	2	3	4	5
2.	Our firm is under pressure from competitors to adopt Big Data Analytics	1	2	3	4	5
3.	Our firm would adopt Big Data Analytics in response to what competitors are doing	1	2	3	4	5

	External support from vendors	Strongly disagree	Disagree	Neither agree nor	Agree	Strongly agree
1.	Community agencies/vendors can provide required training for Big Data adoption.	1	2	3	4	5
2.	Community agencies/vendors can provide effective technical support for Big Data adoption.	1	2	3	4	5
3.	Vendors actively market Big Data adoption.	1	2	3	4	5

	Governmental Support	Strongly disagree	Disagree	Neither agree nor	Agree	Strongly agree
1.	The governmental policies encourage us to adopt new information technology (e.g., big data).	1	2	3	4	5
2.	The government provides incentives for using big data analytics in government procurements and contracts such as offering technical support, training, and funding for big data.	1	2	3	4	5
3.	There are some business laws to deal with the security and privacy concerns over the Big Data technology	1	2	3	4	5

SECTION 6: Organizational Innovativeness

Please indicate to what extent the following statements describe the Organizational Innovativeness when adopting big data in your company.

	Organizational Innovativeness	Strongly disagree	Disagree	Neither agree nor	Agree	Strongly agree
1.	Our company frequently tries out new ideas.	1	2	3	4	5

2.	Our company seeks out new ways to do things.	1	2	3	4	5
3.	Our company is creative in its methods of operation.	1	2	3	4	5
4.	Our company is often the first to market with new products and services.	1	2	3	4	5
5.	Innovation in our company is seen as a valuable opportunity and is actively supported.	1	2	3	4	5
6.	Our new product introduction has increased over the last 5 years.	1	2	3	4	5

The questions in this survey may not have allowed you to report things you may want to say about areas studied in this research. Please make additional comments in the space provided.

Universiti Utara Malaysia

THANK YOU

Sincerely,

Ahmed F. S. Abulehia.

Supervised by:

Dr. Norhaiza bt. Khairudin.

Dr. Mohd Hisham Mohd Sharif.

أخي الفاضل/ أختي الفاضلة

تحية طيبة وبعد،،،

العوامل المؤثرة على تبني استخدام البيانات الضخمة في الشركات الصغيرة والمتوسطة في فلسطين

أنا طالب دكتوراه (رقم جامعي: 903747) تخصص المحاسبة، كلية إدارة اعمال في جامعة شمال ماليزيا، كجزء من دراستي للحصول على درجة الدكتوراه ، أقوم بإجراء استبيان لتحديد العوامل التي تؤثر على تبني البيانات الضخمة في الشركات الصغيرة والمتوسطة في فلسطين.

آمل أن تساعدني في ضمان نجاح هذه الدراسة من خلال استكمال الاستبيان المرفق. إذا كنت ترغب في ذلك ، يمكنك إعطاء هذا الاستبيان لشخص أكثر ملاءمة في الشركة، هذا البحث هو دراسة أكاديمية بحتة. وستبقى جميع المعلومات التي نحصل عليها سرّية للغاية ومجهولة الهوية لن يتم تقديم النتائج إلا في شكل إجمالي ولن يتم تحديد أي نتيجة لشركة واحدة.

أقدر تعاونكم السريع إذا احتجت إلى أي توضيح إضافي، يسعدني مساعدتك، أو يمكنك أيضًا الاتصال بمشرفي كما هو موضح أدناه.

أشكركم مقدماً على لطف تعاونكم

خالص الشكر	اشراف:	اشراف:
أحمد فريد سالم أبو لحية	د. نورهايزا خير الدين	د.محمد هشام محمد شريف
ahmed.abulehia@gmail.com	norhaiza@uum.edu.my	hisham79@uum.edu.my
هاتف: 970599223860+	هاتف: 04-9287298	هاتف 04-9287277

القسم الأول: البيانات الديموغرافية

يرجى وضع إشارة (✔) في مربع الإجابة التي تراها مناسبة:

هل تنوي شركتك استخدام البيانات الضخمة؟

□ نعم □ لا

اذا كانت اجابتك نعم من فضلك استمر بالإجابة عن الاستبيان.

12.تخطط شركتنا استخدام البيانات الضخمة في الفترة المقبلة خلال؟

□ ثلاثة شهور □ ستة شهور □ تسع شهور

□ سنة □ أخرى (يرجى التحديد_____)

13.مَوْقع الشركة في فلسطين ـ قطاع غزة

□ محافظة الشمال □ محافظة غزة □ محافظة الوسطى

□ محافظة خان يونس □ محافظة رفح

14.في أي نوع من القطاعات يقع نشاط شركتك ؟

□ القطاع الصناعي □ قطاع الخدمات □ القطاع التجاري

□ قطاع المقاولات □ أخرى (يرجى التحديد_____)

15.يرجى تقدير عدد الموظفين العاملين بنظام الدوام الكامل في الشركة.

□ 1 – 4 □ 5-19 □ 20 – 49

□ أكثر من 50

16.يرجى تقدير المبيعات السنوية / حجم الأعمال التجارية في الشركة لعام 2020

□ أقل من أو بما يعادل ≤ $ 20,000 □ من $20,001 إلى $200,000

□ من $200,001 إلى $500,000 □ أكثر من $500,000

17.يرجى تقدير رأس مال الشركة المسجل في عام 2020.

□ أقل من أو بما يعادل ≤ $ 5,000 □ من $5001 إلى $50,000

□ من $50,001 إلى $100,000 □ أكثر من $100,000

18.يرجى تحديد عدد سنوات نشاط الشركة.

□ أقل من 5 سنوات □ 5 – 10 سنوات □ 11 – 20 سنوات

□ 21 – 30 سنوات □ 31 – 40 سنوات □ أكثر من 40 سنة

19. **كم سنة عملت في هذه الشركة؟**

□ أقل من 5 سنوات □ 5 – 10 سنوات □ 11 – 20 سنوات

□ 21 – 30 سنة □ أكثر من 30 سنة

20.أعلى مؤهل أكاديمي حصلت عليه؟

□ دبلوم فأقل □ بكالوريوس □ دراسات عليا(ماجستير/ دكتوراه)

□ شهادة مهنية □ أخرى (يرجى التحديد_____)

21.أي من الفئات التالية تصف منصبك الحالي بشكل أفضل؟

□ إدارة عليا □ إدارة وسطى □ خط الإدارة الأول

□ أخرى (يرجى التحديد_____)

22.منذ متى وأنت تشغل المنصب الإداري في هذه الشركة؟

□ أقل من 5 سنوات □ من 5 إلى 10 □ من 11 إلى 20 سنة □ أكثر من 20 سنة سنوات

القسم 2: النية لاستخدام البيانات الضخمة

يرجى توضيح إلى أي مدى تصف نية اعتماد البيانات الضخمة في شركتك.

	نية اعتماد البيانات الضخمة	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	تعتزم شركتنا اعتماد البيانات الضخمة.	1	2	3	4	5
2.	تعتزم شركتنا البدء في استخدام البيانات الضخمة بانتظام في المستقبل.	1	2	3	4	5
3.	ستوصي شركتنا بشدة باستخدام البيانات الضخمة للشركات الأخرى.	1	2	3	4	5
4.	تعتزم شركتنا استخدام البيانات الضخمة في الأشهر القليلة المقبلة.	1	2	3	4	5

القسم 3: العوامل التكنولوجية

يرجى توضيح إلى أي مدى تصف العوامل التكنولوجية عند اعتماد البيانات الضخمة في شركتك.

	الميزة النسبية	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	تعمل البيانات الضخمة على تحسين جودة العمل.	1	2	3	4	5
2.	تجعل البيانات الضخمة العمل أكثر كفاءة.	1	2	3	4	5
3.	البيانات الضخمة تخفض التكاليف.	1	2	3	4	5
4.	تعمل البيانات الضخمة على تحسين خدمة العملاء.	1	2	3	4	5
5.	تجذب البيانات الضخمة مبيعات جديدة لعملاء جدد أو أسواق جديدة.	1	2	3	4	5

Universiti Utara Malaysia

.6	يحدد اعتماد البيانات الضخمة فرص المنتجات / الخدمات الجديدة.	1	2	3	4	5

	التوافق	معارض بشدة	معارض	محايد	موافق	موافق بشدة
.1	توفر البيانات الضخمة بنية مرنة تتوافق مع المهام التحليلية المختلفة.	1	2	3	4	5
.2	تتوافق بنية البيانات الضخمة مع المخططات المستخدمة لتخزين البيانات.	1	2	3	4	5
.3	تتوافق البيانات الضخمة مع البنية التكنولوجية الحالية.	1	2	3	4	5
.4	من السهل مزامنة البيانات الخارجية مع البيانات الداخلية للمنظمة.	1	2	3	4	5

	التعقيد	معارض بشدة	معارض	محايد	موافق	موافق بشدة
.1	من الصعب تطويع كمية هائلة من البيانات غير المهيكلة من مصادر متعددة لجعلها متوافقة مع البيانات المنظمة.	1	2	3	4	5
.2	من الصعب تفسير نتائج تحليل البيانات الضخمة لاستخراج معرفة قابلة للتنفيذ.	1	2	3	4	5
.3	من الصعب دمج البيانات عبر عدة قواعد بيانات غير متوافقة بين مختلف المساهمين.	1	2	3	4	5
.4	من الصعب تكامل البيانات عبر أنظمة معلومات منفصلة.	1	2	3	4	5

	القابلية للتجربة	معارض بشدة	معارض	محايد	موافق	موافق بشدة

Universiti Utara Malaysia

1.	يمكن لشركتنا الوصول إلى نسخة تجريبية مجانية قبل اتخاذ قرار استخدام تحليلات البيانات الضخمة.	1	2	3	4	5
2.	لدى شركتنا الفرصة لتجربة عدد من تطبيقات تحليلات البيانات الضخمة قبل اتخاذ قرار وتجربة حزم برامج تحليلات البيانات الكبيرة على نطاق واسع بما فيه الكفاية.	1	2	3	4	5
3.	يُسمح لشركتنا باستخدام تحليلات البيانات الضخمة على أساس تجريبي لفترة كافية لمعرفة إمكاناتها الحقيقية.	1	2	3	4	5
4.	من السهل الخروج بعد اختبار حزمة تحليلات البيانات الضخمة.	1	2	3	4	5
5.	تكلفة تنصيب تحليلات البيانات الضخمة منخفضة.	1	2	3	4	5

	الملاحظة	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	بدأ العديد من المنافسين أو شركاء الأعمال في السوق باستخدام البيانات الضخمة.	1	2	3	4	5
2.	يساعد استخدام البيانات الضخمة شركتنا على التواصل مع الشركاء المحليين والدوليين.	1	2	3	4	5
3.	يوجد العديد من أجهزة الكمبيوتر التي يمكن للأشخاص في الشركة الوصول إليها لاستخدام البيانات الضخمة.	1	2	3	4	5
4.	تُظهر البيانات الضخمة نتائج أفضل مقارنة بممارسة الأعمال التجارية بالطريقة التقليدية.	1	2	3	4	5

Universiti Utara Malaysia

قسم 4: العوامل التنظيمية

يرجى توضيح إلى أي مدى تصف العوامل التنظيمية عند اعتماد البيانات الضخمة في شركتك.

	دعم الإدارة العليا	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	ستوفر الإدارة العليا الموارد اللازمة لاعتماد البيانات الضخمة.	1	2	3	4	5
2.	ستوفر الإدارة العليا الدعم اللازم لاعتماد البيانات الضخمة.	1	2	3	4	5
3.	ستدعم الإدارة العليا استخدام البيانات الضخمة.	1	2	3	4	5
4.	الإدارة العليا متحمسة بشأن اعتماد البيانات الضخمة.	1	2	3	4	5

	جاهزية المنظمة	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	أدى نقص رأس المال / الموارد المالية إلى منع شركتنا من الاستغلال الكامل للبيانات الضخمة.	1	2	3	4	5
2.	أدى الافتقار إلى البنية التحتية لتكنولوجيا المعلومات إلى منع شركتنا من استغلال البيانات الضخمة.	1	2	3	4	5
3.	إن الافتقار إلى القدرة التحليلية يمنع الشركة من استغلال البيانات الضخمة بالكامل.	1	2	3	4	5
4.	يؤدي نقص الموظفين المهرة إلى عدم استغلال البيانات الضخمة بالكامل.	1	2	3	4	5

Universiti Utara Malaysia

قسم 5: العوامل البيئية

يرجى توضيح إلى أي مدى تصف العوامل البيئية عند اعتماد البيانات الضخمة في شركتك.

	الضغط التنافسي	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	سيتأثر اختيارنا لاعتماد تحليلات البيانات الضخمة بشدة بما يفعله المنافسون في قطاعات الأعمال.	1	2	3	4	5
2.	تتعرض شركتنا لضغوط من المنافسين لاعتماد تحليلات البيانات الضخمة.	1	2	3	4	5
3.	ستتبنى شركتنا تحليلات البيانات الضخمة استجابة لما يفعله المنافسون.	1	2	3	4	5

	الدعم الخارجي من الموردين	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	يمكن لوكالات المجتمع / البائعين تقديم التدريب المطلوب لاعتماد البيانات الضخمة.	1	2	3	4	5
2.	يمكن لوكالات المجتمع / البائعين تقديم دعم فني فعال لاعتماد البيانات الضخمة.	1	2	3	4	5
3.	يسوق البائعون اعتماد البيانات الضخمة بشكل فعال.	1	2	3	4	5

Universiti Utara Malaysia

	الدعم الحكومي	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	تشجع السياسات الحكومية على تبني تكنولوجيا المعلومات الجديدة (مثل البيانات الضخمة).	1	2	3	4	5
2.	تقدم الحكومة حوافز لاستخدام تحليلات البيانات الضخمة في المشتريات والعقود	1	2	3	4	5

	الحكومية مثل تقديم الدعم الفني والتدريب والتمويل للبيانات الضخمة.					
3.	يوجد قوانين ناظمة للشركات للتعامل مع مخاوف الأمان والخصوصية بشأن تقنية البيانات الضخمة.	1	2	3	4	5

قسم 6: الجاهزية الفنية

يرجى توضيح إلى أي مدى تصف الجاهزية الفنية عند اعتماد البيانات الضخمة في شركتك.

	الابتكار المؤسسي	معارض بشدة	معارض	محايد	موافق	موافق بشدة
1.	تجرب شركتنا الأفكار الجديدة بشكل متكرر.	1	2	3	4	5
2.	تسعى شركتنا إلى إيجاد طرق جديدة للقيام بالأشياء.	1	2	3	4	5
3.	تبتكر شركتنا في طرق عملها.	1	2	3	4	5
4.	تكون شركتنا غالباً الأولى في السوق بمنتجات وخدمات جديدة.	1	2	3	4	5
5.	يُنظر إلى الابتكار في شركتنا على أنه فرصة واعدة ويحظى بالدعم.	1	2	3	4	5
6.	لقد زاد تقديم المنتجات الجديدة لدينا خلال السنوات الخمس الماضية.	1	2	3	4	5

ربما لم تسمح لك الأسئلة في هذه الاستبانة بذكر بعض الأشياء التي قد ترغب في قولها حول المجالات التي تمت دراستها في هذا البحث. يرجى إبداء تعليقات إضافية في المساحة المتوفرة أدناه.

Universiti Utara Malaysia

نشكركم لحسن تعاونكم

تحياتي

أحمد فريد أبو لحية

باشراف

د.نور هايزا خيرالدين

د.محمد هشام محمد شريف

Universiti Utara Malaysia

Table: Selected studies related to relative advantage to the intention or adoption of big data

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2023	Abulehia, A.F.S. , Khairudin, N. , Sharif, M.H.M.	Palestine	Intention to Adopt Big Data	TOE	Palestinian Manufacturing SMEs	Owners or Managers (310)	Survey	√	
2.	2023	Baig, M.I. , Yadegaridehkordi, E. , Nizam Bin Md Nasir, M.H.	Malaysia	big data adoption	TOE	manufacturing SMEs in Malaysia	CEO/managers (159)	questionnaire	√	
3.	2022	Lutfi, A. , Al-Khasawneh, A.L. , Almaiah, M.A. , ... Saad, M. , Ali, R.A.	Jordan	big data adoption	TOE & RBV	Small and medium Jordanian hotels	SME hotel owners/managers (119)	online questionnaire survey	√	
4.	2022	Lutfi, A. , Alsyouf, A. , Almaiah, M.A. , ... Ibrahim, N. , Saad, M.	Jordan	big data adoption	TOE & DOI	manufacturing Jordanian SMEs	SMEs owners/managers (116)	online questionnaire survey	√	

Universiti Utara Malaysia

5.	2022	Truong, N.X.	Vietnam	Big Data Adoption	TOE & TAM	SMEs in Vietnam	SMEs owners/managers (372)	direct survey and online	√	
6.	2021	Baig, M.I. , Shuib, L. , Yadegaridehkordi, E.	Pakistan	big data adoption	TOE & DOI	higher education sector	managerial side of virtual university (VU) campuses (195)	online survey questionnaire	√	
7.	2021	Nasrollahi, M. , Ramezani, J. , Sadraei, M.	Iran	big data adoption	/	Iranian SMEs	SMEs senior and middle managers (224)	Survey	√	
8.	2020	Maroufkhani, Tseng, Iranmanesh, Ismail, and Khalid	Iran	Big data Analytics Adoption (BDA)	RBV, TOE	Manufacturing SMEs.	112 Owners or CEO	Survey		√
9.	2020	Sun, Hall, and Cegielski	China	Intention to adopt big data	TOE, DOI & institutional theory	B2B e-service providers	197 IT Managers	Survey	√	
10.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (full sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	√	
11.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	√	

Universiti Utara Malaysia

12.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (non-adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	√
13.	2019	(Park & Kim, 2021)	Korea	Big Data Adoption	TOE	Manufacturing & Service firms	50 experts & 226 companies	face-to-face interviews	√
14.	2019	(Jang, Kim, Jung, and Gim 2019)	Korea	Intention to Introduce Big Data	TOE & DOI	Organizations in different industries and different size	102 experts in Smart Factory and Big Data	Survey	√
15.	2019	(Yadegaridehkordi, Nilashi, Shuib, Hairul, and Bin 2019)	Malaysia	Big data adoption	TOE & Human-Organization-Technology	Hotel Industry	418 top managers and/or owners of SMEs	online survey	√
16.	2018	(Lai, Sun, and Ren 2018)	China	Intention to adopt BDA	TOE	Organizations.	210 IT managers & business analysts	Online Survey	√
17.	2018	(Verma, Bhattacharya, and Kumar 2018)	India	Behavioural intention to use BDA systems	TAM	Organizations.	150 big data analytics users	Online Survey	√

Universiti Utara Malaysia

18.	2018	(Sam and Chatwin 2018)	China	Attitudes towards big data analytics& Intention to use big data analytics	TOE	Organizations in different industries	178 organisational users	Survey	√
19.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	full sample (Manufacturing and se rvices sectors)	478 top and middle-level IT professionals	Online Survey	√
20.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Services Sector	478 top and middle-level IT professionals	Online Survey	√
21.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing sector	478 top and middle-level IT professionals	Online Survey	√
22.	2018	(Mahesh, Vijayapala, and Dasanayaka 2018)	Sri Lanka	The Intention to Adopt Big Data	TOE	licensed finance companies	30 IT managers	self-administered structured questionnair e	+√
23.	2018	(Schüll and Maslan 2018)	Germany	Adoption of Big Data Analytics	TOE & Dynamic Capabilit ies Theory	organisations of different sizes	46 Top Managers	online survey	√

Universiti Utara Malaysia

24.	2018	(Wang et al. 2018)	China	Big Data Adoption	Motivation–Opportunity–Ability (MOA) model	Enterprises	20 experts (scholars, big data application, senior managers,	questionnaires	√
25.	2018	(Lai et al. 2018)	China	Intention to adopt BDA	TOE	Varied industries (manufacturing to high technology)	210 IT managers and business analysts	Online Survey	√
26.	2018	(Yadegaridehkordi et al. 2018)	Malaysia	big data adoption	fuzzy-set theory	Manufacturing Companies	234 industrial managers	online survey	√
27.	2017	(Verma, 2017)	India	Intention to Adopt Big Data Services	-	Manufacturing firms	205 (CEO/COO/CIO/CFO,General Manager, Director, Controller, Manager, Senior Analyst)	Survey	√
28.	2016	(Mneney et al., 2016)	South African	Big Data Capabilities and Readiness	TOE & Task Technology Fit (TTF)	Retail Organizations	8 Big Data vendors and IT professional service providers	Semi structured interviews	√
29.	2015	(Park, Jong-Hyun; Kim, Moon-Koo; Paik 2015)	Korea	Adoption and Usage of Big Data	TOE	experts having 10-year research experience. policy and business in IT sectors including more than 3 years in big data	50 Experts and policy makers	face-to-face interviews	√

30.	2015	(Nam, Kang, and Kim 2015)	Korea	Big data analysis adoption	TOE	(information, financial services, retail/wholesale/manufacturing)	58 Top management team or IS manager	Online Survey		√
31.	2015	(Chen, Preston, and Swink 2015)	Around the World	Big Data Analytics Usage	TOE	Members of the Council of Supply Chain Management Professionals (CSCMP)	161 Supply Chain Managers	a cross-sectional survey	√	
32.	2015	(Agrawal, 2015)	China and India	Big Data Analytics (BDA) Adoption	DOI, TOE, institutional theory	Organizations Across the Industries	106 organisations	Administered survey	√	

*+ The direction of the relationship is positive

Source: Self-illustration

Table: Selected studies related to compatibility and the intention or adoption of big data

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2023	Abulehia, A.F.S. , Khairudin, N. , Sharif, M.H.M.	Palestine	Intention to Adopt Big Data	TOE	Palestinian Manufacturing SMEs	Owners or Managers (310)	Survey	√	

Universiti Utara Malaysia

2.	2022	Lutfi, A. , Al-Khasawneh, A.L. , Almaiah, M.A. , ... Saad, M. , Ali, R.A.	Jordan	big data adoption	TOE & RBV	Small and medium Jordanian hotels	SME hotel owners/managers (119)	online questionnaire survey		√
3.	2022	Lutfi, A. , Alsyouf, A. , Almaiah, M.A. , ... Ibrahim, N. , Saad, M.	Jordan	big data adoption	TOE & DOI	manufacturing Jordanian SMEs	SMEs owners/managers (116)	online questionnaire survey		√
4.	2022	Truong, N.X.	Vietnam	Big Data Adoption	TOE & TAM	SMEs in Vietnam	SMEs owners/managers (372)	direct survey and online	√	
5.	2021	Baig, M.I. , Shuib, L. , Yadegaridehkordi, E.	Pakistan	big data adoption	TOE & DOI	higher education sector	managerial side of virtual university (VU) campuses (195)	online survey questionnaire	√	
6.	2021	Nasrollahi, M. , Ramezani, J. , Sadraei, M.	Iran	big data adoption	/	Iranian SMEs	SMEs senior and middle managers (224)	Survey	√	
7.	2021	Ghaleb, E.A.A. , Dominic, P.D.D. , Fati, S.M. , Muneer, A. , Ali, R.F.	Malaysia	big data adoption	TOE & TRI	Malaysian healthcare sector	Malaysian healthcare employees (302)	survey questionnaire	√	

Universiti Utara Malaysia

8.	2020	(Maroufkhani, Tseng, Iranmanesh, Ismail, and Khalid 2020)	Iran	Big data Analytics Adoption (BDA)	RBV, TOE	Manufacturing SMEs.	112 Owners or CEO	Survey		√
9.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (full sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey		√
10.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey		√
11.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (non-adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey		√
12.	2019	(Park & Kim, 2021)	Korea	Big Data Adoption	TOE	Manufacturing & Service firms	50 experts & 226 companies	face-to-face interviews		√
13.	2019	(Jang, Kim, Jung, and Gim 2019)	Korea	Intention to Introduce Big Data	TOE & DOI	Organizations in different industries and different size	102 experts in Smart Factory and Big Data	Survey	√	
14.	2019	(Yadegarideh kordi, Nilashi, Shuib, Hairul, and Bin 2019)	Malaysia	Big data adoption	TOE & Human-Organization-Technolo	Hotel Industry	418 top managers and/or owners of SMEs	online survey	√	

Universiti Utara Malaysia

					gy				
15.	2018	(Sam and Chatwin 2018)	China	Attitudes towards big data analytics& Intention to use big data analytics	TOE	Organizations in different industries	178 organisational users	Survey	√
16.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	full sample (Manufacturing an d services sectors)	478 top and middle-level IT professionals	Online Survey	√
17.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Services Sector	478 top and middle-level IT professionals	Online Survey	√
18.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing sector	478 top and middle-level IT professionals	Online Survey	√
19.	2018	(Mahesh, Vijayapala, and Dasanayaka 2018)	Sri Lanka	The Intention to Adopt Big Data	TOE	licensed finance companies	30 IT managers	self-administered structured questionnair e	+√

Universiti Utara Malaysia

20.	2018	(Yadegarideh kordi et al. 2018)	Malaysia	big data adoption	fuzzy-set theory	manufacturing companies	234 industrial managers	online survey		√
21.	2016	(Verma and Bhattacharyya 2017)	India	adoption of Big Data Analytics	TOE	different enterprises and service providers (banking, telecommunication, retail, health care, education, service providers)	22 experts different enterprises and service providers	face-to-face semi-structured interviews	√	
22.	2015	(Park, Jong-Hyun; Kim, Moon-Koo; Paik 2015)	Korea	Adoption and Usage of Big Data	TOE	experts having 10-year research experience. policy and business in IT sectors including more than 3 years in big data	50 Experts and policy makers	face-to-face interviews	√	
23.	2015	(Chen, Preston, and Swink 2015)	Around the World	Big Data Analytics Usage	TOE	Members of the Council of Supply Chain Management Professionals (CSCMP)	161 Supply Chain Managers	a cross-sectional survey	√	
24.	2015	(Agrawal, 2015)	China and India	Big Data Analytics (BDA) Adoption	DOI, TOE, institutional theory	Organizations Across the Industries	106 organisations	Administered survey	√	

*+ The direction of the relationship is positive

Source: Self-illustration

Universiti Utara Malaysia

Table: Selected studies related to complexity and the intention or adoption of big data

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2023	Abulehia, A.F.S. , Khairudin, N. , Sharif, M.H.M.	Palestine	Intention to Adopt Big Data	TOE	Palestinian Manufacturing SMEs	Owners or Managers (310)	Survey	√	
2.	2023	Baig, M.I. , Yadegaridehkordi, E. , Nizam Bin Md Nasir, M.H.	Malaysia	big data adoption	TOE	manufacturing SMEs in Malaysia	CEO/managers (159)	questionnaire	-√	
3.	2022	Lutfi, A. , Alsyouf, A. , Almaiah, M.A. , ... Ibrahim, N. , Saad, M.	Jordan	big data adoption	TOE & DOI	manufacturing Jordanian SMEs	SMEs owners/managers (116)	online questionnaire survey	-√	
4.	2022	Truong, N.X.	Vietnam	Big Data Adoption	TOE & TAM	SMEs in Vietnam	SMEs owners/managers (372)	direct survey and online	√	
5.	2021	Baig, M.I. , Shuib, L. , Yadegaridehkordi, E.	Pakistan	big data adoption	TOE & DOI	higher education sector	managerial side of virtual university (VU) campuses (195)	online survey questionnaire	-√	

Universiti Utara Malaysia

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
6.	2021	Nasrollahi, M. , Ramezani, J. , Sadraei, M.	Iran	big data adoption	/	Iranian SMEs	SMEs senior and middle managers (224)	Survey	√	
7.	2021	Ghaleb, E.A.A. , Dominic, P.D.D. , Fati, S.M. , Muneer, A. , Ali, R.F.	Malaysia	big data adoption	TOE & TRI	Malaysian healthcare sector	Malaysian healthcare employees (302)	survey questionnaire		√
8.	2020	(Maroufkhani, Tseng, Iranmanesh, Ismail, and Khalid 2020)	Iran	Big data Analytics Adoption (BDA)	RBV, TOE	Manufacturing SMEs.	112 Owners or CEO	Survey	-√	
9.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (full sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	-√	
10.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	-√	

Universiti Utara Malaysia

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
11.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (non-adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	-√	
12.	2019	(Park & Kim, 2021)	Korea	Big Data Adoption	TOE	Manufacturing & Service firms	50 experts & 226 companies	face-to-face interviews		√
13.	2019	(Jang, Kim, Jung, and Gim 2019)	Korea	Intention to Introduce Big Data	TOE & DOI	Organizations in different industries and different size	102 experts in Smart Factory and Big Data	Survey		√
14.	2019	(Yadegaridehkordi, Nilashi, Shuib, Hairul, and Bin 2019)	Malaysia	Big data adoption	TOE & Human-Organization-Technology	Hotel Industry	418 top managers and/or owners of SMEs	online survey		√
15.	2018	(Lai, Sun, and Ren 2018)	China	Intention to adopt BDA	TOE	Organizations.	210 IT managers & business analysts	Online Survey		√
16.	2018	(Verma, Bhattacharyya, and Kumar 2018)	India	Attitude toward BDA systems	TAM	Organizations.	150 big data analytics users	Online Survey	√	

Universiti Utara Malaysia

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
17.	2018	(Sam and Chatwin 2018)	China	Attitudes towards big data analytics& Intention to use big data analytics	TOE	Organizations in different industries	178 organisational users	Survey	√	
18.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	full sample (Manufacturing and services se ctors)	478 top and middle-level IT professionals	Online Survey	-√	
19.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Services Sector	478 top and middle-level IT professionals	Online Survey	-√	
20.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing sector	478 top and middle-level IT professionals	Online Survey		√
21.	2018	(Mahesh, Vijayapala, and Dasanayaka 2018)	Sri Lanka	The Intention to Adopt Big Data	TOE	licensed finance companies	30 IT managers	self-administered structured questionnaire	-√	
22.	2018	(Wang et al. 2018)	China	Big Data Adoption	Motivation – Opportunit y–Ability (MOA)	Enterprises	20 experts (scholars, big data application, senior managers,	questionnaires	√	

Universiti Utara Malaysia

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
					model					
23.	2018	(Lai et al. 2018)	China	Intention to adopt BDA	TOE	Varied industries (manufacturing to high technology)	210 IT managers and business analysts	Online Survey		√
24.	2018	(Yadegaridehkordi et al. 2018)	Malaysia	big data adoption	fuzzy-set theory	manufacturing companies	234 industrial managers	online survey	√	
25.	2016	(Verma and Bhattacharyya 2016)	India	adoption of Big Data Analytics	TOE	different enterprises and service providers (banking, telecommunication, retail, health care, education, service providers)	22 experts different enterprises and service providers	face-to-face semi-structured interviews	√	
26.	2016	(Mneney & Belle, 2016)	South African	Big Data Capabilities and Readiness	TOE & Task Technology Fit (TTF)	Retail Organizations	8 Big Data vendors and IT professional service providers	Semi structured interviews	√	

Universiti Utara Malaysia

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
27.	2015	(Jong-Hyun; Kim, Moon-Koo; Paik 2015)	Korea	Adoption and Usage of Big Data	TOE	experts having 10-year research experience. policy and business in IT sectors including more than 3 years in big data	50 Experts and policy makers	face-to-face interviews	√	
28.	2015	(Agrawal, 2015)	China and India	Big Data Analytics (BDA) Adoption	DOI, TOE, institutional theory	Organizations Across the Industries	106 organisations	Administered survey	-√	

*- the direction of relationship is negative

Source: Self-illustration

Universiti Utara Malaysia

Table: Selected Studies Related to Top Management Support Variable.

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2023	Abulehia, A.F.S. , Khairudin, N. , Sharif, M.H.M.	Palestine	Intention to Adopt Big Data	TOE	Palestinian Manufacturing SMEs	Owners or Managers (310)	Survey	√	
2.	2023	Baig, M.I. , Yadegaridehkordi, E. , Nizam Bin Md Nasir, M.H.	Malaysia	big data adoption	TOE	manufacturing SMEs in Malaysia	CEO/managers (159)	questionnaire	√	
3.	2021	Bakici, T. , Nemeh, A. , Hazir, O.	French	big data adoption	TOE	French companies in 11 different industries	project manager (16)	semi structured interviews with one project manager	√	
4.	2023	Sharma, M. , Gupta, R. , Sehrawat, R. , Jain, K. , Dhir, A.	India	big data adoption	TOE	India's top 20 firms	28 industry experts	Semi-structured interviews and	√	

Universiti Utara Malaysia

								multi-criteria decision-making (MCDM)	
5.	2022	Lutfi, A. , Al-Khasawneh, A.L. , Almaiah, M.A. , ... Saad, M. , Ali, R.A.	Jordan	big data adoption	TOE & RBV	Small and medium Jordanian hotels	SME hotel owners/managers (119)	online questionnaire survey	√
6.	2022	Lutfi, A. , Alsyouf, A. , Almaiah, M.A. , ... Ibrahim, N. , Saad, M.	Jordan	big data adoption	TOE & DOI	manufacturing Jordanian SMEs	SMEs owners/managers (116)	online questionnaire survey	√
7.	2022	Truong, N.X.	Vietnam	Big Data Adoption	TOE & TAM	SMEs in Vietnam	SMEs owners/managers (372)	direct survey and online	√
8.	2021	Baig, M.I. , Shuib, L. , Yadegaridehkordi, E.	Pakistan	big data adoption	TOE & DOI	higher education sector	managerial side of virtual university (VU) campuses	online survey questionnaire	√

							(195)		
9.	2021	Nasrollahi, M. , Ramezani, J. , Sadraei, M.	Iran	big data adoption	/	Iranian SMEs	SMEs senior and middle managers (224)	Survey	√
10.	2021	Ghaleb, E.A.A. , Dominic, P.D.D. , Fati, S.M. , Muneer, A. , Ali, R.F.	Malaysia	big data adoption	TOE & TRI	Malaysian healthcare sector	Malaysian healthcare employees (302)	survey questionnaire	√
11.	2020	(Maroufkhani, Tseng, Iranmanesh, Ismail, and Khalid 2020)	Iran	Big data Analytics Adoption (BDA)	RBV, TOE	Manufacturing SMEs.	112 Owners or CEO	Survey	√
12.	2020	(Sun, Hall, and Cegielski 2020)	China	Intention to adopt big data	TOE, DOI & institutiona l theory	B2B e-service providers	197 IT Managers	Survey	√
13.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (full sample)	231 CIOs,CTOs directors, senior business and IS	Online Survey	

Universiti Utara Malaysia

							managers	
14.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey
15.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (non-adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey
16.	2019	(Park & Kim, 2021)	Korea	Big Data Adoption	TOE	Manufacturing & Service firms	50 experts & 226 companies	face-to-face interviews
17.	2019	(Jang, Kim, Jung, and Gim 2019)	Korea	Intention to Introduce Big Data	TOE & DOI	Organizations in different industries and different size	102 experts in Smart Factory and Big Data	Survey

Universiti Utara Malaysia

18.	2019	(Yadegaridehkordi, Nilashi, Shuib, Hairul, and Bin 2019)	Malaysia	Big data adoption	TOE & Human-Organization-Technology	Hotel Industry	418 top managers and/or owners of SMEs	online survey	
19.	2018	(Lai, Sun, and Ren 2018)	China	Intention to adopt BDA	TOE	Organizations.	210 IT managers & business analysts	Online Survey	
20.	2018	(Sam and Chatwin 2018)	China	Attitudes towards big data analytics& Intention to use big data analytics	TOE	Organizations in different industries	178 organisational users	Survey	
21.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing and services sectors	478 top and middle-level IT professionals	Online Survey	+√
22.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Services Sectors	478 top and middle-level IT professionals	Online Survey	+√

Universiti Utara Malaysia

23.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing sector	478 top and middle-level IT professionals	Online Survey	+√
24.	2018	(Schüll and Maslan 2018)	Germany	Adoption of Big Data Analytics	TOE & Dynamic Capabilities Theory	organisations of different sizes	46 Top Managers	online survey	√
25.	2018	(Wang et al. 2018)	China	Big Data Adoption	Motivation – Opportunity–Ability (MOA) model	Enterprises	20 experts (scholars, big data application, senior managers,	questionnaires	√
26.	2018	(Lai et al. 2018)	China	Intention to adopt BDA	TOE	Varied industries (manufacturing to high technology)	210 IT managers and business analysts	Online Survey	√
27.	2018	(Yadegaridehkordi et al. 2018)	Malaysia	big data adoption	fuzzy-set theory	manufacturing companies	234 industrial managers	online survey	√

Universiti Utara Malaysia

28.	2016	(Verma and Bhattacharyya 2016)	India	adoption of Big Data Analytics	TOE	different enterprises and service providers (banking, telecommunication, retail, health care, education, service providers)	22 experts different enterprises and service providers	face-to-face semi-structured interviews	√
29.	2016	(Mneney & Belle, 2016)	South African	Big Data Capabilities and Readiness	TOE & Task Technology Fit (TTF)	Retail Organizations	8 Big Data vendors and IT professional service providers	Semi structured interviews	√
30.	2015	(Park, Jong-Hyun; Kim, Moon-Koo; Paik 2015)	Korea	Adoption and Usage of Big Data	TOE	Experts having 10-year research experience. policy and business in IT sectors including more than 3 years in big data	50 Experts and policy makers	face-to-face interviews	√

*+ the direction of relationship is positive

Universiti Utara Malaysia

Table: Selected Studies Related to Organizational Readiness Variable.

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2023	Abulehia, A.F.S. , Khairudin, N. , Sharif, M.H.M.	Palestine	Intention to Adopt Big Data	TOE	Palestinian Manufacturing SMEs	Owners or Managers (310)	Survey	√	
2.	2023	Baig, M.I. , Yadegaridehkordi, E. , Nizam Bin Md Nasir, M.H.	Malaysia	big data adoption	TOE	manufacturing SMEs in Malaysia	CEO/managers (159)	questionnaire	√	
3.	2022	Lutfi, A. , Al-Khasawneh, A.L. , Almaiah, M.A. , ... Saad, M. , Ali, R.A.	Jordan	big data adoption	TOE & RBV	Small and medium Jordanian hotels	SME hotel owners/managers (119)	online questionnaire survey	√	
4.	2022	Lutfi, A. , Alsyouf, A. , Almaiah, M.A. , ... Ibrahim, N. , Saad, M.	Jordan	big data adoption	TOE & DOI	manufacturing Jordanian SMEs	SMEs owners/managers (116)	online questionnaire survey	√	
5.	2023	Maroufkhani, P. Iranmanesh, M. Ghobakhloo, M.	Iran	big data adoption	TOE	Manufacturing SMEs.	171 owner/managers	online spurvey		√

Universiti Utara Malaysia

6.	2020	Maroufkhani, P. Wan Ismail, W.K. Ghobakhloo, M. 2020	Iran	Big data Analytics Adoption (BDA)	RBV, TOE	Manufacturing SMEs.	112 Owners or CEO	Survey	√	
7.	2020	(Maroufkhani, Tseng, Iranmanesh, Ismail, and Khalid 2020)	Iran	Big data Analytics Adoption (BDA)	TOE & DOI, RBV	171 Iranian small and medium manufacturing	171 owner/managers	online spurvey	√	
8.	2020	(Yadegaridehkordi, Nilashi, Shuib, Hairul, and Bin 2019)	Malaysia	Big data adoption	TOE & Human-Organization-Technology	Hotel Industry	418 top managers and/or owners of SMEs	online survey	√	
9.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	full sample (Manufacturing and services sectors)	478 top and middle-level IT professionals	Online Survey		√
10.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Services Sector	478 top and middle-level IT professionals	Online Survey		√
11.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing Sector	478 top and middle-level IT professionals	Online Survey		√
12.	2015	(Chen, Preston, and Swink 2015)	USA	Big Data Analytics Usage	TOE	Members of the Council of Supply Chain Management Professionals	161 Supply Chain Managers	a cross-sectional survey	√	

Universiti Utara Malaysia

Table: Selected Studies Related to Competitive Pressure Variable.

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2023	Abulehia, A.F.S. , Khairudin, N. , Sharif, M.H.M.	Palestine	Intention to Adopt Big Data	TOE	Palestinian Manufacturing SMEs	Owners or Managers (310)	Survey	√	
2.	2022	Lutfi, A. , Alsyouf, A. , Almaiah, M.A. , ... Ibrahim, N. , Saad, M.	Jordan	big data adoption	TOE & DOI	manufacturing Jordanian SMEs	SMEs owners/managers (116)	online questionnaire survey		√
3.	2021	Baig, M.I. , Shuib, L. , Yadegaridehkordi, E.	Pakistan	big data adoption	TOE & DOI	higher education sector	managerial side of virtual university (VU) campuses (195)	online survey questionnaire	√	
4.	2020	(Maroufkhani, Tseng, Iranmanesh, Ismail, and Khalid 2020)	Iran	Big data Analytics Adoption (BDA)	RBV, TOE	Manufacturing SMEs.	112 Owners or CEO	Survey		√
5.	2020	(Sun, Hall, and Cegielski 2020)	China	Intention to adopt big data	TOE, DOI & institutional theory	B2B e-service providers	197 IT Managers	Survey	√	

Universiti Utara Malaysia

6.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (full sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	√	
7.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	√	
8.	2019	(Verma & Chaurasia, 2019)	Indian	Big Data Analytics Adoption	TOE	Firms (non-adopter sub-sample)	231 CIOs,CTOs directors, senior business and IS managers	Online Survey	√	
9.	2019	(Park & Kim, 2021)	Korea	Big Data Adoption	TOE	Manufacturing & Service firms	50 experts & 226 companies	face-to-face interviews		√
10.	2019	(Jang, Kim, Jung, and Gim 2019)	Korea	Intention to Introduce Big Data	TOE & DOI	Organizations in different industries and different size	102 experts in Smart Factory and Big Data	Survey	√	
11.	2019	(Yadegaridehkordi, Nilashi, Shuib, Hairul, and Bin 2019)	Malaysia	Big data adoption	TOE & Human-Organization - Technology	Hotel Industry	418 top managers and/or owners of SMEs	online survey	√	
12.	2018	(Lai, Sun, and Ren 2018)	China	Intention to adopt BDA	TOE	Organizations.	210 IT managers & business analysts	Online Survey	√	

Universiti Utara Malaysia

13.	2018	(Sam and Chatwin 2018)	China	Attitudes towards big data analytics& Intention to use big data analytics	TOE	Organizations in different industries	178 organisational users	Survey	√	
14.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing a nd services sect ors	478 top and middle-level IT professionals	Online Survey	+√	
15.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Services Sectors	478 top and middle-level IT professionals	Online Survey	+√	
16.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing sectors	478 top and middle-level IT professionals	Online Survey	+√	
17.	2018	(Mahesh, Vijayapala, and Dasanayaka 2018)	Sri Lanka	The Intention to Adopt Big Data	TOE	licensed finance companies	30 IT managers	self-administered structured questionnaire	+√	
18.	2018	(Schüll and Maslan 2018)	Germany	Adoption of Big Data Analytics	TOE & Dynamic Capabilities Theory	organisations of different sizes	46 Top Managers	online survey		√

Universiti Utara Malaysia

19.	2018	(Wang et al. 2018)	China	Big Data Adoption	Motivation–Opportunity –Ability (MOA) model	Enterprises	20 experts (scholars, big data application, senior managers,	questionnaires	√
20.	2018	(Yadegaridehkordi et al. 2018)	Malaysia	big data adoption	fuzzy-set theory	manufacturing companies	234 industrial managers	online survey	√
21.	2016	(Verma and Bhattacharyya 2016)	India	adoption of Big Data Analytics	TOE	different enterprises and service providers (banking, telecommunication, retail, health care, education, service providers)	22 experts different enterprises and service providers	face-to-face semi-structured interviews	√
22.	2016	(Mneney & Belle, 2016)	South African	Big Data Capabilities and Readiness	TOE & Task Technology Fit (TTF)	Retail Organizations	8 Big Data vendors and IT professional service providers	Semi structured interviews	√
23.	2015	(Park, Jong-Hyun; Kim, Moon-Koo; Paik 2015)	Korea	Adoption and Usage of Big Data	TOE	experts having 10-year research experience. policy and business in IT sectors including more than 3 years in big data	50 Experts and policy makers	face-to-face interviews	√

Universiti Utara Malaysia

24.	2015	(Nam, Kang, and Kim 2015)	Korea	Big data analysis adoption	TOE	(information, financial services, retail/wholesale/ manufacturing)	58 Top management team or IS manager	Online Survey		√
25.	2015	(Chen, Preston, and Swink 2015)	USA	Big Data Analytics Usage	TOE	Members of the Council of Supply Chain Management Professionals (CSCMP)	161 Supply Chain Managers	a cross-sectional survey	√	
26.	2015	(Agrawal, 2015)	China and India	Big Data Analytics (BDA) Adoption	DOI, TOE, institutional theory	Organizations Across the Industries	106 organisations	Administered survey	√	

*+ the direction of relationship is positive

Universiti Utara Malaysia

Table: Selected Studies Related to External Support from Vendors Variable.

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2022	Truong, N.X.	Vietnam	Big Data Adoption	TOE & TAM	SMEs in Vietnam	SMEs owners/managers (372)	direct survey and online	√	
2.	2022	Nguyen, G.T. , Liaw, S.-Y. , Duong, X.-L.	Vietnam	big data adoption	TRI	Vietnamese SMEs manufacturing and service sectors	CEO, IT managers, SMEs managers (274)	online questionnaires	√	
3.	2021	Nasrollahi, M. , Ramezani, J. , Sadraei, M.	Iran	big data adoption	/	Iranian SMEs	SMEs senior and middle managers (224)	Survey	√	
4.	2020	Maroufkhani, P. Wan Ismail, W.K. Ghobakhloo, M. 2020	Iran	Environmental Context àBig data Analytics Adoption (BDA)	RBV, TOE	Manufacturing SMEs.	112 Owners or CEO	Survey	√	
5.	2020	(Maroufkhani, Tseng, Iranmanesh, Ismail, and Khalid 2020)	Iran	Big data Analytics Adoption (BDA)	TOE & DOI, RBV	171 Iranian small and medium manufacturing	171 owner/managers	online spurvey	√	

Universiti Utara Malaysia

6.	2019	(Yadegaridehkordi, Nilashi, Shuib, Hairul, and Bin 2019)	Malaysia	Big data adoption	TOE & Human-Organization - Technology	Hotel Industry	418 top managers and/or owners of SMEs	online survey	√
7.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing and services sectors	478 top and middle-level IT professionals	Online Survey	√
8.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Services Sector	478 top and middle-level IT professionals	Online Survey	√
9.	2018	(Gangwar, 2018)	India	Big Data Adoption	TOE	Manufacturing sector	478 top and middle-level IT professionals	Online Survey	√
10.	2016	(Mneney & Belle, 2016)	South African	Big Data Capabilities and Readiness	TOE & Task Technology Fit (TTF)	Retail Organizations	8 Big Data vendors and IT professional service providers	Semi structured interviews	√

*+ the direction of relationship is positive

Universiti Utara Malaysia

Table: Selected Studies Related to Governmental Support Variable.

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2023	Baig, M.I. , Yadegaridehkordi, E. , Nizam Bin Md Nasir, M.H.	Malaysia	big data adoption	TOE	manufacturing SMEs in Malaysia	CEO/managers (159)	questionnaire	√	
2.	2022	Lutfi, A. , Al-Khasawneh, A.L. , Almaiah, M.A. , ... Saad, M. , Ali, R.A.	Jordan	big data adoption	TOE & RBV	Small and medium Jordanian hotels	SME hotel owners/managers (119)	online questionnaire survey	√	
3.	2022	Lutfi, A. , Alsyouf, A. , Almaiah, M.A. , ... Ibrahim, N. , Saad, M.	Jordan	big data adoption	TOE & DOI	manufacturing Jordanian SMEs	SMEs owners/managers (116)	online questionnaire survey	√	
4.	2022	Nguyen, G.T. , Liaw, S.-Y. , Duong, X.-L.	Vietnam	big data adoption	TRI	Vietnamese SMEs manufacturing and service sectors	CEO, IT managers, SMEs managers (274)	online questionnaires	√	
5.	2021	Baig, M.I. , Shuib, L. , Yadegaridehkordi, E.	Pakistan	big data adoption	TOE & DOI	higher education sector	managerial side of virtual university (VU) campuses (195)	online survey questionnaire	√	

Universiti Utara Malaysia

6.	2021	Ghaleb, E.A.A. , Dominic, P.D.D. , Fati, S.M. , Muneer, A. , Ali, R.F.	Malaysia	big data adoption	TOE & TRI	Malaysian healthcare sector	Malaysian healthcare employees (302)	survey questionnaire	√	
7.	2023	Maroufkhani, P. Iranmanesh, M. Ghobakhloo, M.	Iran	big data adoption	TOE	Manufacturing SMEs.	171 owner/managers	online spurvey		√
8.	2020	(Sun, Hall, and Cegielski 2020)	China	Intention to adopt big data	TOE, DOI & institutional theory	B2B e-service providers	197 IT Managers	Survey	√	
9.	2019	(Park & Kim, 2021)	Korea	Big Data Adoption	TOE	Manufacturing & Service firms	50 experts & 226 companies	face-to-face interviews	√	
10.	2019	(Jang, Kim, Jung, and Gim 2019)	Korea	Intention to Introduce Big Data	TOE & DOI	Organizations in different industries and different size	102 experts in Smart Factory and Big Data	Survey	√	
11.	2018	(Lai, Sun, and Ren 2018)	China	Intention to adopt BDA	TOE	Organizations.	210 IT managers & business analysts	Online Survey	√	
12.	2018	(Sam and Chatwin 2018)	China	Attitudes towards big data analytics& Intention to use big data	TOE	Organizations in different industries	178 organisational users	Survey	√	

Universiti Utara Malaysia

				analytics					
13.	2018	(Mahesh, Vijayapala, and Dasanayaka 2018)	Sri Lanka	The Intention to Adopt Big Data	TOE	licensed finance companies	30 IT managers	self-administered structured questionnaire	+√
14.	2018	(Yadegaridehkordi et al. 2018)	Malaysia	big data adoption	fuzzy-set theory	manufacturing companies	234 industrial managers	online survey	√
15.	2016	(Mneney & Belle, 2016)	South African	Big Data Capabilities and Readiness	TOE & Task Technology Fit (TTF)	Retail Organizations	8 Big Data vendors and IT professional service providers	Semi structured interviews	√
16.	2015	(Park, Jong-Hyun; Kim, Moon-Koo; Paik 2015)	Korea	Adoption and Usage of Big Data	TOE	experts having 10-year research experience. policy and business in IT sectors including more than 3 years in big data	50 Experts and policy makers	face-to-face interviews	√
17.	2015	(Agrawal, 2015)	China and India	Big Data Analytics (BDA) Adoption	DOI, TOE, institutional theory	Organizations Across the Industries	106 organisations	Administered survey	-√

*+ the direction of relationship is positive

Universiti Utara Malaysia

Table: Selected Studies Related to Organizational Innovativeness in different context.

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
1.	2023	(Shahadat et al., 2023)	Bangladesh	ICT adoption	TOE, DOI	SMEs in Bangladesh	Higher- and middle-level managers of SMEs	a structured questionnaire	√	
2.	2021	Saleem Malik ,Mehmood Chadhar ,Savanid Vatanasakdakul and Madhu Chetty	Australia	Adoption of Blockchain Technology	TOE	Adopters and potential adopter organisations	196 CTO, IT directors/managers	online survey	√	
3.	2020	Lin, Jiabao Luo, Zhimei Luo, Xin	China	E-business transformation intention	Institutional theory	agricultural firms	437 managers	survey	√	
4.	2019	Arash Asiaei and Nor Zairah Ab. Rahim	Malaysia	Intention to adopt cloud computing	TOE, DOI, TAM	SMEs in Malaysia	SMEs' managers 209	survey	√	
5.	2018	Kim et al. (2018)	Korea	Semantic Web Technology Adoption	TOE, IDT	Firms from different sectors	IT professionals' perspective 235	online survey	√	

Universiti Utara Malaysia

NO	Year	Source	Country	DV	Model	Domain	Sample/ Unit of Analysis	Data collection	Result	
									Sig	Insig
6.	2015	Fariba Safari	Iran	Cloud computing adoption	TOE	Iranian SMEs	SMEs' managers 92	Online questionnaire survey		√
7.	2013	Yazn Alshamaila, Savvas Papagiannidis, Feng Li,	The north east of England	Cloud computing adoption	TOE	SMEs and service providers	SMEs' managers 15	semi-structured interviews	√	
8.	2007	Nabeel Al-Qirim	New Zealand	1-External-email adoption. 2-Adoption of Web sites	Innovation Diffusion Theory (IDT)	SMEs in NZ	SMEs' managers 129	survey questionnaires	√	

Universiti Utara Malaysia