BUSINESS INTELLIGENCE ADOPTION INTENTION AMONG SMALL START-UP OWNERS: EXAMINING THE INFLUENCING FACTORS OF BENEFITS, SACRIFICE, PERCEIVED-VALUE, AND DESIRE

WONG CHI TIN

UNIVERSITI SAINS MALAYSIA

2022

BUSINESS INTELLIGENCE ADOPTION INTENTION AMONG SMALL START-UP OWNERS: EXAMINING THE INFLUENCING FACTORS OF BENEFITS, SACRIFICE, PERCEIVED-VALUE, AND DESIRE

by

WONG CHI TIN

Thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

September 2022

ACKNOWLEDGEMENT

To begin with, I would like to express the appreciation to my supervisor Associate Professor Dr. Tan Cheng Ling, from the Graduate School of Business (GSB) at the Universiti Sains Malaysia (USM) and my co-supervisor Associate Professor Dr. Imran Mahmud, from the Department of Information Technology and Management, Daffodil International University. Without their care, support, guidance and patient, I am not able to finish my PhD thesis. I am so lucky to have them in my PhD journey. I still remember at the beginning of my PhD journey, I did not have a strong background in doing research in the field of Information System. Every time when I went into a wrong direction, they guide me back to the right direction and spend time to discuss with me to correct my wrong concepts. Doing research with them is one of the unforgettable moment in my life. I learnt a lot of research skills form them and it has been an honor to be their student. Also, I would like to dedicate this thesis to my parents. By their encouragement, prayers, affection, sacrifice and love of days and nights make me able to solve any difficulties during my PhD journey. Also, in the past years, they help me a lot in cooking, house cleaning and other housework so that I can fully concentrate on doing research. They are the best parents in the world. Finally, I would like to thank the members of the judge panel of my viva-voce. They are professional scholars in the world and I really appreciate them spend time to read my PhD thesis and give me a lot valuable and useful comments to make my thesis better.

TABLE OF CONTENTS

| ACK | NOWLE | DGEMENT ii |
|------|------------|---|
| TABI | LE OF C | ONTENTS iv |
| LIST | OF TAB | LES ix |
| LIST | OF FIG | URES xi |
| LIST | OF ABB | REVIATIONSxii |
| ABS | ΓRAK | xiii |
| ABS | ΓRACT . | xvi |
| СНА | PTER 1 | INTRODUCTION1 |
| 1.1 | Introduc | tion |
| 1.2 | Backgro | ound of the Study |
| | 1.2.1 | Global Market of BI system |
| | 1.2.2 | Benefits of BI system |
| | 1.2.3 | A critique of the BI system |
| | 1.2.4 | Start-ups Culture in Hong Kong |
| | 1.2.5 | BI adoption problems in the context of Hong Kong Start-ups 16 |
| 1.3 | Problem | Statement |
| 1.4 | Research | h questions |
| 1.5 | Research | h objectives |
| 1.6 | Scope of | f study |
| 1.7 | Significa | ance of the study |
| | 1.7.1 | Theoretical Significance |
| | 1.7.2 | Practical Significance |
| | 1.7.3 | Methodological Significance |
| 1.8 | Definition | on of key terms |
| 1.9 | Summar | y and organization of the remaining chapters |
| СНА | PTER 2 | LITERATURE REVIEW 41 |
| 2.1 | Introduc | tion |
| 2.2 | Major th | neories of technology adoption intention related to BI |

| | 2.2.1 | Technolog | y Acceptance Model (TAM) | 43 |
|-----|----------|--------------|------------------------------------|----|
| | | 2.2.1(a) | Origin | 43 |
| | | 2.2.1(b) | TAM and BI | 46 |
| | 2.2.2 | DeLone an | d McLean IS Success Model | 48 |
| | | 2.2.2(a) | Origin | 48 |
| | | 2.2.2(b) | IS success and BI | 51 |
| | 2.2.3 | Technolog | y, Organization, Environment (TOE) | 53 |
| | | 2.2.3(a) | Origin | 53 |
| | | 2.2.3(b) | TOE and BI | 54 |
| | 2.2.4 | Value-base | ed Adoption Model (VAM) | 56 |
| | | 2.2.4(a) | Origin | 56 |
| | | 2.2.4(b) | VAM and BI | 58 |
| 2.3 | A review | v of motivat | ion theories | 60 |
| | 2.3.1 | Motivation | theory | 61 |
| | 2.3.2 | Maslow's | Need Hierarchy Theory | 63 |
| | 2.3.3 | Herzberg's | Motivation Hygiene Theory | 64 |
| | 2.3.4 | McClellan | d's Needs Theory | 66 |
| | 2.3.5 | Alderfer's | ERG Theory | 67 |
| | 2.3.6 | Vroom's E | xpectancy theory | 69 |
| | 2.3.7 | Adam's Ec | quity Theory | 71 |
| | 2.3.8 | Goal Settin | ng Theory | 73 |
| | 2.3.9 | Reinforcer | nent Theory | 74 |
| | 2.3.10 | Summary | of motivational theories | 76 |
| 2.4 | BI adopt | tion studies | in past two decades | 78 |
| | 2.4.1 | Main antec | redents | 83 |
| 2.5 | Research | h Gaps | | 86 |
| 2.6 | Research | h Model Dev | velopment | 94 |
| | 2.6.1 | Underlying | g theories | 96 |
| | | 2.6.1(a) | Value-based Adoption Model | 96 |
| | | 2.6.1(b) | Expectancy Theory | 98 |

| | 2.6.2 | Constructs | identification | | |
|-----|------------------|---------------|--|--|--|
| | | 2.6.2(a) | Constructs from theory 1: Value-based Adoption Model 100 | | |
| | | 2.6.2(b) | Constructs from theory 2: Expectancy theory | | |
| | | 2.6.2(c) | Constructs for theories connection | | |
| | | 2.6.2(d) | Desire to make good decision as mediator between rewards and | | |
| | | | BI adoption intention | | |
| | | 2.6.2(e) | Perceived value as a mediator between benefit-sacrifice | | |
| | | | constructs and adoption intention | | |
| 2.7 | Summar | y of this cha | apter | | |
| СНА | PTER 3 | RESEAI | RCH METHODOLOGY126 | | |
| 3.1 | Introduc | tion | | | |
| 3.2 | Research | h paradigm | | | |
| 3.3 | Research | h Design | | | |
| 3.4 | Samplin | g | | | |
| | 3.4.1 | Sampling t | technique | | |
| | 3.4.2 | Sample Siz | ze | | |
| | 3.4.3 | Data collec | ction procedure | | |
| 3.5 | Survey | questionnair | e development | | |
| | 3.5.1 | Demograp | hic questionnaire | | |
| | 3.5.2 | Instrument | t development | | |
| | 3.5.3 | Pre-test | | | |
| 3.6 | Data preparation | | | | |
| | 3.6.1 | Missing D | ata | | |
| | 3.6.2 | Common I | Method Variance (CMV) | | |
| 3.7 | Data ana | alysis techni | ques | | |
| | 3.7.1 | Model spe | cification | | |
| | 3.7.2 | Outer mod | lel evaluation | | |
| | | 3.7.2(a) | Composite Reliability (CR) | | |
| | | 3.7.2(b) | Average Variance Extracted (AVE) | | |
| | | 3.7.2(c) | Discriminant Validity (Fornell and Larcker) | | |

| | | 3.7.2(d) | Discriminant Validity (HTMT) | 170 |
|-----|-----------|---------------|---|-------|
| | 3.7.3 | Inner mode | el evaluation | 171 |
| | | 3.7.3(a) | Coefficient of Determination (R ²) | 171 |
| | | 3.7.3(b) | Cross-validated Redundancy (Q ²) | 172 |
| | | 3.7.3(c) | Path Coefficient | 172 |
| | | 3.7.3(d) | Effect Size (f ²) | 173 |
| 3.8 | Data ana | alysis tools | | 174 |
| | 3.8.1 | Google She | eet | . 174 |
| | 3.8.2 | Google For | m | 175 |
| | 3.8.3 | Statistical I | Product and Service Solutions (SPSS) | 175 |
| | 3.8.4 | SmartPLS | 3.2.9 | 176 |
| 3.9 | Summar | y of research | n methodology | 177 |
| CHA | PTER 4 | DATA AN | NALYSIS | 180 |
| 4.1 | Introduc | tion | | 180 |
| 4.2 | Pre-test | result | | 181 |
| 4.3 | Data pre | paration | | 182 |
| | 4.3.1 | Missing va | lue analysis | 182 |
| | 4.3.2 | Common M | Method Variance test result | . 182 |
| | | 4.3.2(a) | Harman's single factor test | 183 |
| | | 4.3.2(b) | Marker Variable | 184 |
| 4.4 | Target re | espondents a | nd demographic information | 185 |
| 4.5 | Outer m | odel evaluati | on | 189 |
| | 4.5.1 | Item loadin | g, mean and standard deviation | . 189 |
| | 4.5.2 | Cronbach's | Alpha, Average Variance Extracted and Composite | |
| | | Reliability | | 192 |
| | 4.5.3 | Discrimina | nt Validity | 193 |
| | | 4.5.3(a) | Fornell and Larcker criteria | 193 |
| | | 4.5.3(b) | Heterotrait-Monotrait Ratio (HTMT) | 194 |
| 4.6 | Inner mo | odel evaluati | on | 195 |
| | 161 | Coefficient | of determination (\mathbf{P}^2) | 105 |

| | 4.6.2 | Predictive relevance (Q ²) | 196 |
|------|-----------|---|-------|
| | 4.6.3 | Path coefficient (β) and hypothesis test result | 197 |
| | 4.6.4 | Effect size | 204 |
| 4.7 | Final res | search model | 206 |
| СНА | PTER 5 | DISCUSSION AND CONCLUSION | 209 |
| 5.1 | Introduc | tion | 209 |
| 5.2 | Recapitu | ulation and Summary of the Research | 209 |
| 5.3 | Discussi | on on findings | 211 |
| | 5.3.1 | Predictors of perceived value | 212 |
| | 5.3.2 | Relationship between perceived value and adoption intention | 216 |
| | 5.3.3 | Predictors of desire to make good decision | 218 |
| | 5.3.4 | Relationship between desire to make good decision and adoption | |
| | | intention | . 220 |
| | 5.3.5 | Relationship between perceived value, desire and adoption intention | 221 |
| | 5.3.6 | Relationship between rewards, desire to make good decision and adoption | on |
| | | intention | 222 |
| | 5.3.7 | Relationship between benefit-sacrifice constructs, perceived value and | |
| | | adoption intention | 224 |
| 5.4 | Contribu | ations and implications | 226 |
| | 5.4.1 | Theoretical contribution | 226 |
| | 5.4.2 | Practical Contributions | 228 |
| | 5.4.3 | Methodological contributions | 232 |
| 5.5 | Limitati | ons | 234 |
| 5.6 | Future re | esearch | 235 |
| 5.7 | Conclus | ion | 236 |
| REF | ERENCE | S | .239 |
| APPI | ENDICES | S | |
| LIST | OF PUB | LICATIONS | |

LIST OF TABLES

| | | Page |
|------------|---|------|
| Table 2.1 | D&M Model Construct Descriptions | 49 |
| Table 2.2 | Different between VAM and TAM | 56 |
| Table 2.3 | McClelland's three central motivational paradigms | 67 |
| Table 2.4 | Theories used in BI adoption in past two decades | 79 |
| Table 2.5 | Number of BI adoption study in different perspective | 90 |
| Table 2.6 | Summary of Literature Gaps | 94 |
| Table 2.7 | Summary of hypothesis | 124 |
| Table 3.1 | Comparison between Phenomenological and Positivist | 129 |
| Table 3.2 | Reason behind quantitative method | 130 |
| Table 3.3 | Response rate in some literature related to Hong Kong | 138 |
| Table 3.4 | Items of perceived benefits dimension | 146 |
| Table 3.5 | Items of perceived sacrifice dimension | 150 |
| Table 3.6 | Items of perceived value | 152 |
| Table 3.7 | Items of desire to make good decision | 154 |
| Table 3.8 | Items of adoption intention | 155 |
| Table 3.9 | Procedural remedies for CMV in this study | 161 |
| Table 3.10 | Statistical remedies for CMV in this study | 162 |
| Table 3.11 | Marker variables in this study | 163 |
| Table 3.12 | Reasons behind adoption of PLS-SEM | 165 |
| Table 3.13 | Summary of research methodology in this study | 177 |
| Table 4.1 | Comparison between baseline model and marker included model . | 184 |
| Table 4.2 | Respondent's demographic information | 186 |
| Table 4.3 | Company's demographic information | 188 |
| Table 4.4 | Item loading, mean and standard deviation | 190 |
| Table 4.5 | Measurement Model Results | 192 |
| Table 4.6 | Fornell and Larcker Criteria | 193 |
| Table 4.7 | HTMT Criteria | 195 |
| Table 4.8 | Coefficient of Determination | 196 |
| Table 4.9 | Predictive Relevance | 196 |
| Table 4.10 | Path coefficient and hypothesis test result | 197 |
| Table 4 11 | Mediation effect analysis of H13 | 200 |

| Table 4.12 | Mediation effect analysis of H14 and H15 | .201 |
|------------|--|------|
| Table 4.13 | Mediation effect analysis of H16 and H17 | .202 |
| Table 4.14 | Strength of effect | .205 |
| Table 4.15 | Summary of research findings | .207 |

LIST OF FIGURES

| | | Page |
|-------------|---|------|
| Figure 1.1 | Market Share of BI systems in 2021 | 4 |
| Figure 1.2 | Enterprise Application Software Forecast, 2018-2023 | 6 |
| Figure 1.3 | The number of start-ups in Hong Kong | 15 |
| Figure 1.4 | BI adoption rate in small size organization in recent years | 20 |
| Figure 2.1 | Theories of Technology Adoption Intention | 43 |
| Figure 2.2 | Technology Acceptance Model | 45 |
| Figure 2.3 | D&M Model | 51 |
| Figure 2.4 | Technology, Organization, Environment (TOE) | 52 |
| Figure 2.5 | Value-based Adoption Model (VAM) | 57 |
| Figure 2.6 | Theories of motivation | 61 |
| Figure 2.7 | Maslow's Hierarchy of Needs | 64 |
| Figure 2.8 | ERG Theory | 68 |
| Figure 2.9 | Explanation of Expectancy Theory | 70 |
| Figure 2.10 | Explanation of Equity Theory | 73 |
| Figure 2.11 | Explanation of goal-setting Theory | 74 |
| Figure 2.12 | Positive and negative stimuli related to BI adoption | 85 |
| Figure 2.13 | Research Gap on perceived value and desire | 93 |
| Figure 2.14 | Research Model | 123 |
| Figure 3.1 | Research Paradigm in this study | 127 |
| Figure 3.2 | G*power Setting | 137 |
| Figure 3.3 | Data collection procedure | 139 |
| Figure 3.4 | Q-Sort example | 157 |
| Figure 3.5 | Outer model of this study | 167 |
| Figure 3.6 | Inner model of this study | 171 |
| Figure 4.1 | Final research model with result | 207 |

LIST OF ABBREVIATIONS

AVE Average Variance Extracted

BI Business Intelligence

CB-SEM Covariance-based Structural Equation Modeling

CMV Common Method Variance

CR Composite Reliability

D&M DeLone and McLean Information System Success Model

DOI Diffusion of Innovation Theory

EM Expectation Maximization

ET Expectancy Theory

IOT Internet of Thing

IT Information Technology

IS Information System

ISR Information System Research

ICT Information and Communication Technology

JMIS Journal of Management Information System

KMS Knowledge Management System

MAP Maximum A Posterior

MI Mean Imputation

MISQ Management Information System Quarterly

OLAP Online Analytical Processing

PLS Partial Least Squares
RBV Resource-Based View

SEM Structural Equation Modeling

SET Social Exchange Theory

SME Small and Medium Enterprises
TAM Technology Acceptance Model

TOE Technology, Organization, Environment Theory

TPB Theory of Planned Behavior
TRA Theory of Reasoned Action

UTAUT Unified Theory of Acceptance and Use of Technology

VAM Value-Based Adoption Model

HASRAT MENGADAPTASI KEPINTARAN PERNIAGAAN ANTARA PEMILIK SYARIKAT PERMULAAN KECIL: PENELITIAN TERHADAP MANFAAT, PENGORBANAN, NILAI TANGGAPAN DAN KEHENDAKAN SEBAGAI FAKTOR-FAKTOR PENGARUHAN

ABSTRAK

Perniagaan permulaan di Hong Kong selalu menghadapi cabaran yang tinggi dan persaingan yang hebat. Kadar kegagalan syarikat permulaan adalah sangat tinggi. Sekira-kira 90 peratus daripada syarikat permulaan akan menamatkan perniagaan dalam tempoh empat bulan pertama. Punca utamanya seperti salah sangka produk boleh ditangani oleh risikan perniagaan yang boleh memberikan maklumat yang berguna dan arahan untuk pembuat keputusan dengan berkesan dan cekap, dan mengurangkan ketidakpastian semasa proses membuat keputusan. Manakala kadar penggunaan risikan perniagaan di Hong Kong adalah kurang daripada negara-negara lain di rantau Asia, Eropah dan Amerika Utara, terutamanya dalam permulaan skala kecil. Oleh itu, cadangan kajian ini adalah untuk mengkaji pengaruh faktor faedah dan faktor pengorbanan terhadap nilai persepsi mengadaptasi BI, menyiasat peranan nilai persepsi antara faktor faedah dan niat menggunakan BI serta faktor pengorbanan dan niat menggunakan BI, meneliti pengaruh ganjaran tidak ketara dan nyata terhadap keinginan untuk membuat keputusan yang baik, mengkaji pengaruh nilai persepsi dan keinginan untuk membuat keputusan yang baik terhadap niat niat menggunakan BI, dan mengkaji pengaruh nilai persepsi terhadap keinginan untuk membuat keputusan yang baik. Kerangka kajian ini mengintegrasikan Model Penerapan Berasaskan Nilai dan Teori Jangkaan. Data dikumpul daripada 177 pemilik permulaan di Hong Kong yang mempunyai pemahaman tentang risikan perniagaan dan tidak menggunakan risikan perniagaan dalam operasi harian mereka. Kajian ini menggunakan pendekatan soal selidik tinjauan dan data dianalisis oleh Smart-PLS Structural Equation Modeling. Keputusan analisis menunjukkan perhubungan yang signifikan bagi faktor faedah (persepsi kebergunaan, ganjaran ketara dan ganjaran tidak ketara) dan faktor pengorbanan (persepsi teknikaliti, persepsi yuran and persepsi risiko prestasi) terhadap persepsi nilai; perhubungan ganjaran ketara dan ganjaran tidak ketara terhadap keinginan untuk membuat keputusan yang baik; perhubungan yang signifikan bagi nilai yang dirasakan dan keinginan untuk membuat keputusan yang baik mengenai niat pakai. Analisis juga mendedahkan peranan pengantara separa keinginan untuk membuat keputusan yang baik antara nilai yang dirasakan dan niat mengguna pakai BI; keinginan untuk membuat keputusan yang baik mengantara sepenuhnya hubungan antara pembolehubah tidak bersandar (ganjaran ketara dan ganjaran tidak ketara) dan niat mengguna pakai BI; dan nilai yang dirasakan sepenuhnya menjadi pengantara hubungan antara enam pembolehubah tidak bersandar (persepsi kebergunaan, ganjaran ketara, ganjaran tidak ketara, persepsi teknikaliti, persepsi yuran, persepsi risiko prestasi) dan niat mengguna pakai BI. Kajian ini menghasilkan implikasi teori dan praktikal, menunjukkan batasan kajian ini dan mencadangkan beberapa hala tuju baharu untuk diterokai oleh penyelidik dalam penyelidikan akan datang.

BUSINESS INTELLIGENCE ADOPTION INTENTION AMONG SMALL START-UP OWNERS: EXAMINING THE INFLUENCING FACTORS OF BENEFITS, SACRIFICE, PERCEIVED-VALUE, AND DESIRE

ABSTRACT

There is a large swath of challenges and stiff competition the start-up company faces in starting a business in Hong Kong. About 90 per cent of start-ups failed within the first four months, and the significant causes of failure, such as product mistiming, can be addressed by business intelligence that can provide useful information and directions for decision-makers to make a decision effectively and efficiently and reduce the uncertainty during the decision-making process. In comparison, the adoption rate of business intelligence in Hong Kong is less than in other countries, especially in small scale start-ups. This study aims to examine the influence of benefits variables and sacrifice variables on the perceived value of adopting BI, and investigate the mediating role of perceived value on the relationship between benefits and BI adoption intention; and between sacrifices and BI adoption intention. This study also examines the influence of intangible and tangible rewards on the desire to make a good decision; examine the influence of perceived value and the desire to make a good decision on BI adoption intention, and examine the influence of perceived value on the desire to make a good decision. The proposed model of this study underlined the Value-based Adoption Model and Expectancy Theory. The data was collected from 177 start-up owners in Hong Kong using a survey questionnaire approach and analyzed by Smart-PLS Structural Equation Modeling. The analysis results indicate a significant relationship of benefit variables (perceived usefulness, tangible rewards and intangible rewards) on perceived value; a significant relationship of sacrifice variable (perceived technicality, perceived fee and perceived performance risk) on perceived value; a significant relationship of tangible rewards and intangible rewards on the desire to make a good decision; the significant relationship of perceived value and the desire to make a good decision on adoption intention. The results revealed that the desire to make a good decision partially mediates the relationship between perceived value and BI adoption intention. The desire to make a good decision has shown a full mediation influence on the relationship between independent variables (tangible rewards and intangible rewards) and BI adoption intention; and perceived value fully mediate the relationship between benefits and sacrifice independent variables and BI adoption intention. This doctoral thesis also acknowledges the limitations of the study and suggests new directions for future research.

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter aims to provide the foundation information of this research study, and the content is organized into seven parts. The background of the study is discussed in the first part, which includes the global market of Business Intelligence (BI) system, benefits of BI system, a critique of BI system, start-ups culture in Hong Kong, and BI adoption problems in the context of Hong Kong start-ups. The second part discussed the problem statement. The third and fourth parts focused on the research questions and objectives, respectively. The fifth part is related to the significance of this study. The sixth part introduced the definition of key terms of this study. The summary and organization of the remaining chapters are introduced in the seventh part.

1.2 Background of the Study

With the rapid development of information technology and today's globally connected economy, numerous sophisticated enterprise software systems available in the market

are used to manage the business sector. These sophisticated enterprise software systems can perform the measurement, analysis, and improvement on business activities, thus that to improve the overall business performance. It also assists organizations to handle a huge amount of information generated in today's business world and transform this information into knowledge that supports management to make better decision, leading to higher competitive advantages. A business intelligence (BI) system is one of the sophisticated software systems for enterprises.

The concept of BI system was first proposed in the late 1990s (Chen, Chiang et al. 2012; Wixom and Watson 2010). BI system is a decision support system (data driven) that integrates data collecting, storage, and analysis and provides business-driven information and results-oriented information (Tanko and Musiliudeen 2012). A BI system is not a single component. However, it is commonly known as a set of technological solutions (Surajit, Umeshwar et al. 2011) that convert data into information to better support the decision-making and provides a platform for the organization to handle a huge amount of data so that organization can gather, integrate and analyze the data to understand better their weaknesses, strengths and opportunities (Harrison, Parker et al. 2015). The adoption of BI can enhance the competitiveness of

a business organization in today's highly competitive business environment and it is one of the vital elements in determining a business organization's success apart from politics, environment and sociology elements.

1.2.1 Global Market of BI system

With the large swath of challenging and heavy competition from both traditional and online businesses, the business intelligence system plays an important role in organizational success. It helps to improve organizations' managerial practices, performance, products and services (Mohamed, Philip et al. 2013; Trieu 2017). Therefore, the demand for business intelligence is increasing nowadays (Heinrichs and Lim 2003; Gartner 2015), and most business organizations across the globe have adopted it. According to the Gartner (2017) Business Intelligence and Analytics Trends report, business intelligence has a market worldwide. In 2017, the worldwide business intelligence market has increased about 7.3 percent, with revenues up to the US \$18.3 billion, and it is predicted that the revenues will reach the US \$22.8 billion by the end of 2020 (Gartner 2017). It explained that executives realize that accurate and timely knowledge can improve business performance (Fayyad, Piatetsky-Shapiro et al. 1996; Gatignon and Xuereb 1997; Bahrami, Arabzad et al. 2012). Therefore, many companies are now deploying business intelligence systems to seek out and interpret the data at hand (Watson and Wixom 2007). In 2018, about 65 percent of the BI application and global Analytics market was shared by the top ten Analytics and BI application vendors, achieving nearly \$13.9 billion in subscription, maintenance, and license revenue (Albert et al. 2019). Of the market shares, Microsoft Power BI is the leading BI application, followed by Tableau Desktop, Qlik Sense, SAP Analytics Cloud, IBM Cognos Analytics, Looker, MicroStrategy Analytics, Sisense and Oracle Analytics Server (TrustRadius, 2021). Figure 1.1 shows the overall market share of BI applications in 2021.

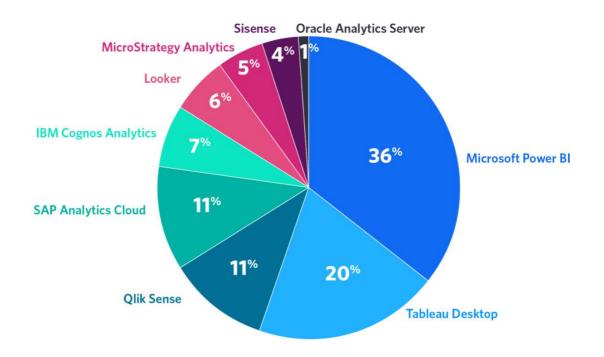


Figure 1.1. Market Share of BI systems in 2021 (TrustRadius, 2021)

The market share distribution data in the above figure shows that Microsoft Power BI holds about 36 percent of the total market, Tableau Desktop holds about 20 percent, Qlik Sense holds about 11 percent, SAP Analytics Cloud holds about 11 percent, IBM Cognos Analytics holds about 7 percent, Looker holds about 6 percent, MicroStrategy Analytics holds about 5 percent, Sisense holds about 4 percent, Oracle Analytics Server holds about 1 percent of the total market.

Albert et al. (2019) worldwide Enterprise Application spending forecast projected enterprise applications spending is expected to grow to about \$ 300 billion in 2023, up from about \$265 billion in 2018. Of the IT spending, the overall market for BI systems is one of the popular fields according to the 2018-2023 compound annual growth (CAGR). Figure 1.2 shows the Enterprise Application Forecast for the period from 2018 to 2023.



Figure 1.2. Enterprise Application Software Forecast, 2018-2023 (Albert et al., 2019)

The investment in BI systems is getting high in today's business environment, the potential risk of failure is also increasing at the same time (Audzeyeva and Hudson 2016; Ain et al. 2019). Therefore, Information system researchers were focused on BI research in order to minimize the potential risk of BI system failure. Ain et al. (2019) showed that BI-related research had increased in the past two decades. The number of research articles related to BI has increased exponentially in recent decades (Ain et al. 2019). According to Google Scholar search result as of Dec 2020, between 2000 and 2020, it showed more than 10000 search results on BI systems.

1.2.2 Benefits of BI system

Nowadays, business organizations generate huge amounts of information every second, such as sales records and customer browsing records. Both industry and academia have shown interest in improving BI's capability to handle the data, integrate BI with other process management activities, and find an approach to increase the penetration rate of BI within an organization (Aina et al. 2019). This is because the information is one of the major competitive factors, and it plays an important role in today's business world (Aleš, Ray et al. 2012). Information can be transformed into knowledge that supports executive' to make a better decision (Bucher, Gericke et al. 2009), which leadss executive to make a better decision (Bucher, Gericke et al. 2009), leading to higher competitive advantages.

To put it simply, BI is a combination of three basic tools: data warehouse, online analytical processing (OLAP), and dashboards. The operation process of BI system is first to collect detailed and accurate data from different sources to data warehouse for further analysis in depth. (Yoon 2008). While online analytical processing (OLAP) is used to support real-time analysis in multidimensional and also allows end-users to explore different details such as products, customers, times, country and region by roll up, drill down, aggregation and filtering (Bach, Čeljo et al. 2016; Thomas, Mary et al.

2007). All the information will be shown on the dashboard. The dashboard is a data visualization application for executives to monitor the business's key performance indicators by creating real-time reports, charts, graphs, and widgets. (Thomas, Mary et al. 2007). In other words, BI system can enhance an organisation's business performance and increase its competitiveness in the market by formulating new business strategies according to the market (Bahrami, Arabzad et al. 2012).

Moreover, the BI system is not exclusive to large scale business organizations. Medium scale business organizations, small scale business organizations and even small-scale start-ups can still deploy BI to support the decision process in four main aspects. The first aspect is to facilitate more aggregation, manage unstructured and structured data, and perform systematic integration. The second aspect is to handle a large amount of data, such as Big Data. The third aspect is increasing users' processing capabilities to discover new knowledge (Wieder and Ossimitz 2015). The fourth aspect is to offer analysis solutions, real time queries, reporting and forecasting (Grublješič and Jaklič 2015; Yoon, Ghost et al. 2014). Researchers also categorized BI systems

into three types, which are strategic BI, tactical BI and operational BI (Oyeniyi and Abiodun 2010; Shollo and Galliers 2015; Huang and Kechad 2013; Gartner 2012).

The main difference between these three types of BI systems is the frequency of data analysis and the granularity of the data being analyzed. Strategic BI application aims to provide new insights to support the long-term organization objectives and goals. Tactical BI application is developed for business analysts and executives whose are responsible for accessing and analyzing data to make short term business decisions. Operational BI application is used in daily business operations to better manage and optimize the process in order to respond to unexpected situations in the operational world.

One of the most important functions of BI to analyse huge amount of data is data mining (Bahrami, Arabzad et al. 2012). Data mining aims to find out valuable information within a huge amount of data (Fayyad, Piatetsky-Shapiro et al. 1996) by using different statistical analysis methods and machine learning techniques. Researchers (Thomas, Mary et al. 2007) stated that BI systems are quite similar to the concept of the original decision support system. They both are a part of management support systems and extend the categories of users, and support broader decisions. The

aim of these two systems is to allow decision maker to make decision effectively and efficiently and also reduce the uncertainty during the decision-making process (Thomas, Mary et al. 2007).

1.2.3 A critique of the BI system

Nevertheless, although business intelligence has growing investment and great market expansion, some studies emphasize that there are a large number of companies fail to obtain benefits from the implemented business intelligence system (Audzeyeva and Hudson 2016). Above 70% of business intelligence projects fail to yield the expected returns (Gartner 2015). In some severe cases, it had tiny or no benefits for organizations (Yeoh and Popovič 2016). The major reason of the failure is primarily due to the complexity of BI system. BI system is required to integrate with the existing information systems in an organization as multi-layered systems and process a huge amount of data. If the multi-layered systems have major usability problems, it can provide less effective functionality (Ceaparu et al., 2004). The complexity of the multilayered systems in an organization can also create confusion, frustration and failure, which leads the negative responses from end-user and they may be made mistakes

when using the systems, and it may affect the business performance of a business organization (Hohmann 2003; Ceaparu et al. 2004). Therefore, many organizations are actively finding the best way to maximize the value from the business intelligence system to make their implementation a success (Visinescu, Jones et al. 2017).

Moreover, because of the complexity of the functions and interface provided by BI systems, end-users must have a basic understanding of different data processing algorithms. For those end-users who do not experience using information systems before and are not really familiar with big data analytics and data mining, it is difficult for them to maximize the value outputted from BI system. This is the main force to resist BI adoption in organisations in today's business world. This situation caught the attention of IS Researchers in past few decades. IS Researchers published hundreds of studies to debate tactical and strategic ways to successfully adopt and use business intelligence systems. A group of researchers (Jourdan, Rainer et al. 2008) reviewed business intelligence studies between 1997 to 2006 focusing on the topic related to research strategies and methods. The second group of researchers (Fitriana, Eriyatno et al. 2011) reviewed business intelligence studies between 2001 to 2011. They underlined that there are two most popular research approaches in business intelligence: the single approach and the integrated approach. They also concluded that 50 percent of research used a single approach and discussed the architecture, methodology, theory and definition of business intelligence systems. While the remaining studies focused on business intelligence integration with other areas, such as artificial intelligence, customer relationship management and supply chain management. The third group of researchers analyzed business intelligence studies between 2000 to 2015 to understand how organizations can obtain value from business intelligence systems.

1.2.4 Start-ups Culture in Hong Kong

In recent years, start-up culture is getting more and more popular in Hong Kong because Hong Kong is one of the world's international financial centres and it provides various economies support such as low taxation, almost free port trade (WeHub 2018). Hong Kong is also ranked 1st as the freest economy globally, and starting business in Hong Kong is safe, easy, and fast (WeHub 2018). Therefore, starting a business in Hong Kong is the first choice in enterprisers' heart. A start-up is a small-scale company in the first stage of operations and small in staffing and revenue. Start-up can be considered as a small size company under the category of SME in Hong Kong.

According to the Hong Kong Trade and Industry Department (2020), "Manufacturing enterprises with fewer than 100 employees and non-manufacturing enterprises with fewer than 50 employees are regarded as small and medium enterprises (SMEs) in Hong Kong". Committee for Economic Development (1974) suggested that a company can be considered as small size if it meets two or more of the following criteria: "(1) Usually the manager is also the owner and the important decision such as the adoption of information systems are usually made by a single individual (e.g. owner) (Khalifa & Davison 2006); (2) Capital is supplied and ownership is held by an individual or a small group; (3) The area of operations is mainly local. Workers and owners are in one home community. Markets need not be local; (4) Relative size within the industry - the business is small when compared with the biggest unit in its field." Although the characteristics between start-up and small size companies are similar, the difference between them is that the years of establishment of start-up are usually less than 3 years (Global Entrepreneurship Monitor 2020), which is in the very first stage of operations. Start-ups are often bankrolled by their entrepreneurial founders initially since they found the needs in the market and aim to develop a service or product to fulfill the needs in the market. Start-up owners are also the

manager/decision maker of the company usually who are responsible for making decision. Most of these small-scale start-ups are not able to operate in the long term without additional funding from the entrepreneurial founders or venture capitalists because of the high operation costs and limited revenue.

The results of government surveys (InvestHK 2020) showed continued increases in the number of start-ups in Hong Kong, it has risen by 51 percent over the 2017 figure. There are 3360 start-ups in Hong Kong currently (InvestHK 2020). Figure 1.3 illustrates the number of start-ups in Hong Kong in recent years.

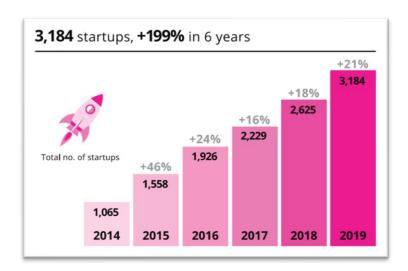


Figure 1.3. The number of start-ups in Hong Kong (InvestHK, 2019; 2020)

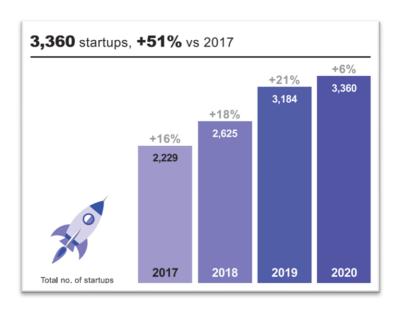


Figure 1.3 (Con't). The number of start-ups in Hong Kong (InvestHK, 2019; 2020)

The above data shows that there are 1065 start-ups in Hong Kong in 2014, 1558 start-ups in Hong Kong in 2015 (increased 46 percent when comparing to previous year), 1926 start-ups in Hong Kong in 2016 (increased 24 percent when comparing to previous year), 2229 start-ups in Hong Kong in 2017 (increased 16 percent when comparing to previous year), 2625 start-ups in Hong Kong in 2018 (increased 18 percent when comparing to previous year), 3184 start-ups in Hong Kong in 2019 (increased 21 percent when comparing to previous year), and 3360 start-ups in Hong Kong in 2020 (increased 6 percent when comparing to previous year).

For the composition of Hong Kong start-up owners, in terms of gender diversity, the majority are male, 55% of start-up owners are male, and the remaining 45% are

female (WeHub 2018). In terms of nationality, 69% of start-up owners are Hong Kong locals, 26% of the start-up owners are non-locals from different countries and territories such as Canada, France, Australia, United States, United Kingdom and Mainland China, among others, and the remaining 5% owners are Hong Kong returnees (InvestHK 2020). In terms of the age group of start-up owners, young adults aged 25-34 and 35-44 are mostly likely to start a new business (WeHub 2018), and with an overall improved perception of entrepreneurship, more and more young adults are seeing start-up as a long-term career.

1.2.5 BI adoption problems in the context of Hong Kong Start-ups

It is understood that starting business in Hong Kong is highly competitive, and it has a large swath of challenges and a heavy amount of competition in previous session. Meanwhile, according to CB insight (2019) research, researchers tracked about 1027 start-ups for a year to monitor their status. At the end of the research, only 1 percent can survival, 22 percent of them merged and 77 percent of them dead, on average, 9 out of 10 start-ups fail (industry standard). Another research also highlighted that about 90 percent of start-ups end in failure within the first four months (about 120 days), 36

percent of the remaining start-ups fail in the second year, 44 percent of the remaining start-ups fail in the third year and 50 percent of the remaining start-ups fail in the fourth year (Small Biz Trends 2019). It shows that the failure rate of start-ups is extremely high. The major causes of start-up failure include product mistiming, price and costing issues, retail stores are dominating a large share of the market giantly, little to market for services or products, lack of customer service, poor online marketing, poor team, lack of online search visibility, got outcompeted and running out of cash. (CB insight 2019). Most of these problems can be addressed by business intelligence mostly because business intelligence can make future prediction based on the historical data, the more data you have on hand, and the more accuracy prediction results can be obtained (Alnoukari 2022). It can provide useful information and directions such as rooms of improvement in real-time for decision-maker of a business organization to make decision effectively and efficiently by using the information given by business intelligence as a reference, it can reduce the uncertainty during the decision-making process (Chen and Lin 2021; Yiu et al. 2021). It can also enhance the business performance of an organization and increase its competitiveness in the market by formulating new business strategies according to the market and to deliver the right products or services to the right person at the right time at the right price (Huang et al. 2022; Alnoukari 2022), which can help an organization to survive in a highly competitive business environment. However, the trend implies that start-ups fail to adopt business intelligence and failed to use its full potential.

Business intelligence has been used widely in business practice and science. Nowadays, there are a wide range of free or charge data analyses tools are available on the Internet that offers historical and predictive data analyses. The problem is whether start-up owners are willing to take advantage of these available resources to spur better decision making. According to Inkwood Research (2018), the global BI market segmented on the basis of four major regions: North America, Asia Pacific, Europe, and Rest of World. The market of BI in Asia Pacific region such as China, Hong Kong, South Korea and Japan is in medium low level, which is less than other countries in North American region (very high level) and Europe region (high level) such as United States, Canada, United Kingdom and France. At the same time, the BI market of Hong Kong is not outstanding when comparing with other developing countries in Asia region such as India, China and South Korea (Inkwood Research 2018). In the current situation, the North American region dominates the business intelligence market, followed by Europe region. The Business Intelligence market in North America region is expected to hold the largest share by 2026. In other words, the adoption rate of BI in Hong Kong is less than North American region and Europe region. There is no doubt that it will decrease the competitive of Hong Kong start-up companies and it is difficult to compete and win in a rapidly evolving global business environment because companies in other regions adopted BI already in their daily operations while Hong Kong start-up companies still not.

Moreover, researchers also investigated the relationship between BI's adoption and the number of employees in an organization (Agostino et al. 2013). The adoption rate is about 8.4 percent (for 1 to 4 employees' organizations), 18.3 percent (for 5 to 9 employees' organizations), 38.8 percent (for 10 to 19 employees' organizations), 43.8 percent (for 50 to 99 employees' organizations), which reflect that when the organization size is small, the adoption rate of BI is low correspondingly. For the BI adoption statistics from 2017 to 2019, the adoption rate in small-scale companies including start-ups in these three years is still in the low level, and it is also predicted that the BI adoption rates of this group will not increase a lot in the near future (Dresner Advisort Services 2019). Figure 1.4 illustrates the BI adoption rate in small-sized

organisations, including start-ups, from 2017 to 2019. Without the use of BI system, Hong Kong small-scale start-ups' owners may not be able to make accurate decision in a short period of time to response to the market and thus that start-ups are difficult to survival in today's high competitive global business environment.

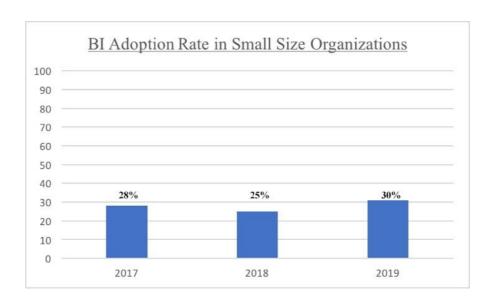


Figure 1.4. BI adoption rate in small size organizations in recent years

(Dresner Advisort Services 2017, 2018, 2019)

International Data Corporation (IDC) highlighted that an organization will obtain and thrive advantages in the competitive market if they make use of business intelligence system to the optimum in their decision-making process. (Villars et al. 2011). It is understood that business intelligence can return some useful insights for decision-maker of an organization to make better and faster decision, which leads to better business performance and help the organization to survival in today's highly

competitive business environment. It is confusing why the adoption rate of business intelligence in small-scale start-up companies is still low? Why are start-ups not willing to adopt BI? What factors are affecting start-ups' adoption intention of business intelligence? Until now, BI vendors are still looking for a solution for factors in influencing the adoption intention of BI among small size company such as start-ups (Aina et al. 2019). While prior scholars paid less attention in identifying a theoretical framework to explain the adoption intention of business intelligence from start-up perspective in the past two decades.

In past two decades, there are a large number of studies related to business intelligence has been conducted in three categories: adoption, utilization and success, these studies are mainly focused on large-scale organizations and middle-scale organizations. (Arefin, Hoque et al. 2015; Arnott, Lizama et al. 2017; Dawson and Belle 2013; Gaardboe, Nyvang et al. 2017). However, to date, the study of the business intelligence adoption intention among start-up business is still at the infancy stage, especially in the context of Hong Kong. As a result, BI system research in the context of Hong Kong is very crucial, a deeper insight into theory-based study is necessary in order to find out the basic barriers and motivators that will affect Hong Kong start-ups

to or restrain them from adopting business intelligence. Therefore, this study aims to make a research inquiry to better understand the adoption intention of BI system among start-ups owners in Hong Kong, and it is expected that this study will be of interest to the start-ups in Hong Kong and BI vendor or other countries with similar situation to Hong Kong where the adoption rate of BI system is not high and the market competition is high.

1.3 Problem Statement

Business intelligence has been used widely in business practice and science. The adoption of BI system can enhance the competitive of a business organization in today's business world. Nowadays, there are a wide range of free or charge data analyses tools are available on the Internet. Despite the growing market for BI system and the potential benefits, the problem is whether start-up owners are willing to take advantage of these available resources to spur better decision making. From the reference (Inkwood Research 2018), the market of BI in Hong Kong is in the middle low level in comparison with North American region (very high level) and Europe region (high level), and it is also predicted that the BI market in North America region

to hold the largest share by 2026. The phenomenon implicit that there are not many companies including start-ups in Hong Kong, adopted BI in their business. Without the use of BI system, start-ups' owners may not be able to make the accurate decision in a short period of time to response to the market and thus that start-up company is difficult to survive in today's highly competitive global business environment. Thus, the investigation on the adoption intention of BI among start-up owners is necessary in order to overcome this situation.

Information System research has become the essential area in technology management sector over the past two decades. Scholars had pointed out that a complex technology like ERP and BI take almost 20 years to be adopted by large scale organization (Aina et al. 2019) and thus that BI vendors are still looking for a solution for factors that influence BI adoption intention in medium scale organizations, small scale organization and start-ups.

There are about 44 research studies (please refer to appendix A) in the past two decades related to BI adoption intention and suggested a lot of information technology adoption intention theories on BI system such as the Technology Acceptance Model (TAM) by Davis et al. (1989), Diffusion of Innovation theory (DOI) by Rogers (1962),

Resource-based view (RBV) by Barney (1991), Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) and Technology, Organization, Environment theory (TOE) by Tornatzky et al. (1990), which have been implemented to measure users' attitude and behavior. Apart from using single theory to explain the adoption intention of BI, researchers also tried to integrate multiple technology adoption intention theories together with theories from psychology, marketing and social science domain such as Theory of Planned Behavior (TPB), Theory of Reasoned Action (TRA), social exchange theory and expectancy theory. However, the above theories used in BI adoption in the past two decades were nottaken into account to measure the user's adoption intention from the perspective of value. Researchers in the past two decades highly rely on TAM to measure the BI adoption and largely ignored other ideas. Of the 44 studies, 15 (34%) used the TAM and its modification as their theoretical framework. Kim et al. (2007) suggested that TAM is too old and insufficient to explain the adoption intention of new information and communication technology such as AI and BI. Thus, Kim et al. (2007) proposed VAM (please see section 2.2.4 for more details) as an alternative model for the TAM, extending TAM's element and solving TAM's limitations in a modern environment.