

**DETERMINANTS OF BIG DATA ANALYTICS  
USAGE AND ITS IMPACT ON PERFORMANCE  
IN CHINESE MANUFACTURING COMPANIES**

**SHI YUBO**

**UNIVERSITI SAINS MALAYSIA**

**2025**

**DETERMINANTS OF BIG DATA ANALYTICS  
USAGE AND ITS IMPACT ON PERFORMANCE  
IN CHINESE MANUFACTURING COMPANIES**

by

**SHI YUBO**

**Thesis submitted in fulfilment of the requirements  
for the degree of  
Doctor of Philosophy**

**January 2025**

## **ACKNOWLEDGEMENT**

There are so many people who deserve my gratitude during my doctoral journey, and I want to emphasize their value here again. First, thank you very much to my supervisor, Professor T. Ramayah, who is a very patient, strict, serious and responsible scholar. He brings me confidence and knowledge and enables me to progress and grow at the beginning of my academic career. Second, I would like to thank my family for their support, which allowed me to devote effort to my studies and finally complete my doctoral journey. Third, I would like to thank the relevant industry authorities and the respondent companies for their support, which allowed my data collection work to proceed smoothly. Finally, I would like to thank the examiners I met during the research process. Their suggestions played an important role in improving my study. Their efforts are very valuable to me.

## TABLE OF CONTENTS

<b>ACKNOWLEDGEMENT .....</b>	<b>ii</b>
<b>TABLE OF CONTENTS .....</b>	<b>iii</b>
<b>LIST OF TABLES .....</b>	<b>xiii</b>
<b>LIST OF FIGURES .....</b>	<b>xv</b>
<b>LIST OF ABBREVIATIONS .....</b>	<b>xvii</b>
<b>LIST OF APPENDICES .....</b>	<b>xix</b>
<b>ABSTRAK .....</b>	<b>xx</b>
<b>ABSTRACT .....</b>	<b>xxii</b>
<b>CHAPTER 1 INTRODUCTION .....</b>	<b>1</b>
1.1 Introduction .....	1
1.2 Background of the Study .....	1
1.2.1 The Importance of Manufacturing in the Economy and Society .....	1
1.2.2 The Importance of BDA in Manufacturing .....	3
1.2.3 The Current State of the BDA in Chinese Manufacturing .....	11
1.3 Problem Statements .....	14
1.3.1 Lack of Competitiveness for China's Manufacturing Industry .....	14
1.3.2 Lack of Research on Big Data Analytics Usage (BDAU) .....	16
1.3.3 Different Internal and External Environments have Different Effects on Company Performance .....	22
1.4 Research Questions .....	25
1.5 Research Objectives .....	26
1.6 Significance of the Study .....	27
1.6.1 Theoretical Significance .....	27
1.6.2 Practical Significance .....	30

1.7	Scope of the Study .....	30
1.8	Operationalization of Key Terms .....	31
1.8.1	Absorptive Capacity .....	31
1.8.2	Acquisition Capacity .....	32
1.8.3	Assimilation Capacity .....	32
1.8.4	BDAU .....	32
1.8.5	Company Size .....	32
1.8.6	Compatibility .....	32
1.8.7	Competitor Pressure .....	33
1.8.8	Complexity .....	33
1.8.9	Cost .....	33
1.8.10	Customer Pressure .....	33
1.8.11	Environmental Dynamism .....	33
1.8.12	Financial Readiness .....	33
1.8.13	Financial Performance .....	34
1.8.14	Expected Benefits .....	34
1.8.15	Exploitation Capacity .....	34
1.8.16	Government Support .....	34
1.8.17	Insecurity Concerns .....	34
1.8.18	IT Infrastructure .....	35
1.8.19	Operational Performance .....	35
1.8.20	Top Management Support .....	35
1.8.21	Transformation Capacity .....	35
1.8.22	Vendor Support .....	36
1.9	Structures of the Remaining Chapters .....	36
1.10	Chapter Summary .....	36

<b>CHAPTER 2</b>	<b>LITERATURE REVIEW .....</b>	<b>37</b>
2.1	Introduction .....	37
2.2	Theoretical Underpinning .....	37
2.2.1	Technology-Organization-Environment (TOE) .....	37
2.2.2	Resource-Based View (RBV) .....	39
2.2.3	Dynamic Capabilities Theory (DCT) .....	40
2.3	Justification of Selected Theories .....	41
2.3.1	Justification for Selection of TOE .....	41
2.3.2	Justification for the Selection of the RBV .....	42
2.3.3	Justification for the Selection of DCT .....	44
2.4	Big Data .....	45
2.4.1	The Definition of Big Data .....	46
2.4.2	The Characteristics of Big Data .....	46
2.4.3	Three Levels of the BDAU .....	48
2.5	BDA .....	50
2.5.1	Definitions of the BDA .....	50
2.5.2	Comparison of Big Data and BDA .....	51
2.6	The Antecedents of BDAU .....	52
2.7	The Outcomes of the BDAU .....	55
2.8	The External and Internal Contexts in Companies .....	56
2.9	Gaps in the Literature .....	58
2.10	Hypothesis development .....	69
2.10.1	Technological Context and BDAU .....	69
2.10.1(a)	Expected Benefits .....	69
2.10.1(b)	Compatibility .....	70
2.10.1(c)	Complexity .....	71
2.10.1(d)	Insecurity Concern .....	72

2.10.1(e) Cost.....	74
2.10.2 Organizational Context and BDAU .....	75
2.10.2(a) Top Management Support .....	75
2.10.2(b) IT Infrastructure .....	76
2.10.2(c) Financial Readiness .....	78
2.10.3 Environmental context and BDAU .....	79
2.10.3(a) Customer Pressure .....	79
2.10.3(b) Vendor Support.....	80
2.10.3(c) Competitive Pressure .....	81
2.10.3(d) Government Support .....	82
2.10.4 Company Performance .....	84
2.10.4(a) Operational Performance .....	84
2.10.4(b) Financial Performance .....	86
2.10.5 Mediator .....	88
2.10.6 Moderator .....	90
2.10.6(a) Environmental Dynamism and Operational Performance .....	91
2.10.6(b) Environmental Dynamism and Financial Performance .....	92
2.10.6(c) Absorptive Capacity and Operational Performance .....	93
2.10.6(d) Absorptive Capacity and Financial Performance .....	94
2.10.7 Control Variable .....	95
2.11 Theoretical Framework .....	99
2.12 Chapter Summary .....	101
<b>CHAPTER 3 METHODOLOGY .....</b>	<b>102</b>
3.1 Introduction .....	102
3.2 Research Paradigm .....	102
3.3 Research Design .....	104

3.4	Research Process .....	106
3.4.1	Defining the Research Problem .....	106
3.4.2	Conducting Literature Review .....	106
3.4.3	Development of a Conceptual Model .....	107
3.4.4	Development of Hypotheses .....	107
3.4.5	Formulating Research Design .....	107
3.4.6	Development of Survey Instruments .....	108
3.4.7	Implementation of Data Collection .....	108
3.4.8	Preparation for Data Analysis .....	108
3.4.9	Analysing and Reporting the Data Results .....	108
3.4.10	Discussion and Conclusions of the Findings .....	109
3.5	Target Population and Sampling Considerations .....	110
3.5.1	Population .....	110
3.5.2	Sample .....	110
3.5.2(a)	Selection of the Sampling Method .....	112
3.5.2(b)	Determining Sample Size .....	116
3.5.2(c)	Implementing the Sampling Plan .....	118
3.5.3	Unit of Analysis .....	120
3.6	Survey Instruments .....	120
3.6.1	Questionnaire Design .....	120
3.6.1(a)	Information Required .....	121
3.6.1(b)	Types of Questions .....	121
3.6.1(c)	Content and Purpose of the Questions .....	122
3.6.1(d)	Types of Responses .....	122
3.6.1(e)	Wording and Language .....	123
3.6.1(f)	Operationalisation and Measurement of Constructs ....	124
3.6.1(g)	Types of Questionnaires .....	132

3.6.1(h)	Structure of the Questionnaire .....	132
3.6.1(i)	Questionnaire Appearance .....	136
3.6.2	Pretesting .....	137
3.6.2(a)	Expert Reviews .....	138
3.6.2(b)	Pilot Study .....	138
3.6.3	Survey Refinement and Final Questionnaire .....	139
3.7	Data Collection Procedure .....	140
3.8	Data Preparation .....	141
3.9	Assessing Multivariate Assumptions .....	141
3.10	Common method variance (CMV) .....	142
3.10.1(a)	Procedural Remedies .....	144
3.10.1(b)	Statistical Remedies .....	146
3.11	Statistical Analysis .....	150
3.11.1	Statistical Analysis via SPSS .....	150
3.11.2	Statistical Analysis via Structural Equation Modelling .....	151
3.11.2(a)	Structural Equation Modelling (SEM) .....	151
3.11.2(b)	Reflective and Formative Measurement Models .....	153
3.11.2(c)	Selection of Partial Least Squares (PLS) or Covariance-Based SEM .....	154
3.11.3	Evaluation of the PLS–SEM Approach Model Results .....	160
3.11.3(a)	Assessment of the Measurement Model .....	161
3.11.3(b)	Assessment of the Structural Model .....	165
3.12	Assessment of Mediation Relationships .....	172
3.12.1	The Quality Criteria for Evaluating the Mediation Model .....	172
3.12.2	Types of Mediating Effects .....	173
3.12.3	Testing Mediating Effects .....	174
3.13	Assessment of the Moderation Relationship .....	174

3.13.1	Quality Criteria for Evaluating the Moderation Model .....	174
3.13.2	Types of Moderator Variables .....	175
3.13.3	Creating the Interaction Term .....	175
3.13.4	Testing Moderating Effects .....	176
3.13.5	Results Interpretation .....	176
3.14	Chapter Summary .....	177
<b>CHAPTER 4 RESULTS .....</b>		<b>179</b>
4.1	Introduction .....	179
4.2	Data preparation .....	179
4.2.1	Data Editing, Coding, and Entry .....	179
4.2.2	Data Screening .....	180
4.2.3	Data Transformation .....	180
4.2.4	Missing Data .....	180
4.2.5	Outliers .....	181
4.3	Assessing Multivariate Assumptions .....	182
4.3.1	Normality .....	182
4.3.2	Normality of Error Terms .....	184
4.3.3	Linearity .....	185
4.3.4	Constant Variance .....	185
4.3.5	Multicollinearity .....	186
4.3.6	Autocorrelation .....	187
4.4	Check of Common Method Variables (CMV) .....	188
4.4.1	Procedural Remedies .....	188
4.4.2	Marker Variable Technique .....	189
4.4.3	Full Collinearity .....	190
4.5	Descriptive Analysis .....	191
4.5.1	Response Rate .....	191

4.5.2	Profile of Respondents .....	192
4.5.3	Descriptive Analysis of the Variables .....	195
4.6	Assessment of the Measurement Model .....	198
4.6.1	Internal Consistency Reliability .....	199
4.6.2	Outer Loadings .....	201
4.6.3	Convergent Validity .....	202
4.6.4	Discriminant Validity .....	202
4.7	Absorptive Capacity was Measured as a Second-order Construct .....	205
4.8	Assessment of the Structural Model .....	209
4.8.1	Examining Collinearity .....	209
4.8.2	Assessing Significance and Relevance .....	209
4.8.3	Control Variable .....	215
4.8.4	Assessing the Explanatory Power of the Model .....	215
4.8.5	Assessing the Predictive Power of the Model .....	217
4.9	Summary .....	218
<b>CHAPTER 5 DISCUSSION AND CONCLUSION .....</b>		<b>219</b>
5.1	Introduction .....	219
5.2	Recapitulation and Summary of Findings .....	219
5.3	Discussion of Findings .....	221
5.3.1	What are the relationships between the technology context and BDAU? .....	221
5.3.1(a)	Expected Benefits .....	221
5.3.1(b)	Compatibility .....	222
5.3.1(c)	Complexity .....	223
5.3.1(d)	Insecurity Concerns .....	224
5.3.1(e)	Cost .....	226
5.3.2	What are the relationships between the organisational context and BDAU? .....	228

5.3.2(a)	Top Management Support .....	228
5.3.2(b)	IT Infrastructure .....	229
5.3.2(c)	Financial Readiness .....	230
5.3.3	What are the relationships between the environmental context and BDAU? .....	232
5.3.3(a)	Customer Pressure .....	232
5.3.3(b)	Vendor Support .....	233
5.3.3(c)	Competitive pressure .....	234
5.3.3(d)	Government Support .....	236
5.3.4	What are the relationships between BDAU and company performance? .....	238
5.3.4(a)	Operational Performance .....	238
5.3.4(b)	Financial Performance .....	239
5.3.5	Does operational performance mediate the relationship between BDAU and financial performance? .....	240
5.3.6	Does environmental dynamism and absorptive capacity moderate the relationship between BDAU and operational performance? .....	242
5.3.6(a)	Environmental Dynamism .....	242
5.3.6(b)	Absorptive Capacity .....	243
5.3.7	Does environmental dynamism and absorptive capacity moderate the relationship between BDAU and financial performance? .....	244
5.3.7(a)	Environmental Dynamism .....	244
5.3.7(b)	Absorptive Capacity .....	245
5.4	Discussion of Findings on Control Variables .....	246
5.5	Theoretical Implications .....	248
5.6	Practical Implications .....	252
5.6.1	Implications for Manufacturing Companies .....	252
5.6.1(a)	Technological Factors .....	253

5.6.1(b)	Organisational Factors .....	257
5.6.1(c)	Environmental Factors .....	258
5.6.1(d)	Company Performance .....	260
5.6.2	Implications for the Developers of the BDA .....	263
5.6.3	Implications for the Government .....	268
5.7	Limitations .....	269
5.8	Directions for Future Studies .....	271
5.9	Summary .....	273
<b>REFERENCES .....</b>		<b>275</b>

**APPENDICES**

**LIST OF PUBLICATIONS**

## LIST OF TABLES

	<b>Page</b>
Table 1.1	Summary of the Role of BDA ..... 8
Table 2.1	The 5 Vs of Big Data ..... 47
Table 2.2	Three Levels of the BDAU ..... 49
Table 2.3	Comparison of Big Data and BDA ..... 51
Table 2.4	The Main Antecedents of BDAU ..... 54
Table 2.5	BDAU Outcomes ..... 56
Table 2.6	Review of the BDAU ..... 60
Table 2.7	Summary of Literature Gaps in the BDAU ..... 68
Table 2.8	Selection of Control Variables ..... 97
Table 2.9	A List of Hypotheses ..... 100
Table 3.1	Comparison of Probability and Nonprobability Sampling for Pros and Cons ..... 114
Table 3.2	Operationalisation and Measurement of the Constructs ..... 125
Table 3.3	Summary of Key Constructs, Sources of Questions, and the Number of Items ..... 135
Table 3.4	Organisation of Multivariate Methods ..... 152
Table 3.5	Rules for Selecting CB-SEM or PLS-SEM ..... 157
Table 3.6	Assessing Reflective Measurement Models ..... 164
Table 3.7	Guidelines for Out-of-sample Predictive Power of the Model ..... 169
Table 3.8	Assessing Structural Models ..... 172
Table 3.9	Types of Mediating Effects ..... 173
Table 3.10	Summary of the Mediation Analyses ..... 174
Table 3.11	Two-stage Approach ..... 175

Table 3.12	Summary of the Moderation Analyses .....	177
Table 4.1	Comparison of the Path Coefficients ( $\beta$ ) between the Baseline Model and the Marker Included in the Model .....	189
Table 4.2	Comparison of $R^2$ between the Vaseline Model and the Model-included Marker .....	190
Table 4.3	Results of the Full Collinearity Test .....	191
Table 4.4	Profile of the Respondents .....	193
Table 4.5	Profiles of Companies .....	195
Table 4.6	Descriptive Analysis Results of the Variables .....	196
Table 4.7	The Results of the Measurement Model .....	199
Table 4.8	The Value of Discriminant Validity .....	204
Table 4.9	Reliability and Validity of Absorptive Capacity .....	206
Table 4.10	Loadings and Cross Loadings .....	207
Table 4.11	Indicator Correlations of OP .....	207
Table 4.12	Indicator Correlations of FP .....	208
Table 4.13	Correlations of the First-order Constructs of Absorptive Capacity .....	208
Table 4.14	Results of the Significance and Relevance .....	211
Table 4.15	Summary of the Hypothesis Tests .....	214
Table 4.16	The $R^2$ of the Constructs .....	215
Table 4.17	Results of the Predictive Power of the Model .....	217

## LIST OF FIGURES

	<b>Page</b>
Figure 1.1	Number of Registered Manufacturing Companies in the Last 10 Years ..... 2
Figure 1.2	Trends in China's Manufacturing Digital Transformation Index ..... 11
Figure 1.3	Number of Companies Recruiting for Digitally Related Positions ... 13
Figure 1.4	Number of Manufacturing Companies Deregistered in the Past 10 Years ..... 15
Figure 1.5	Chinese Manufacturing Heavily Affected by the COVID-19 Outbreak ..... 24
Figure 2.1	Theoretical Framework ..... 99
Figure 3.1	Summary of the Research Process ..... 109
Figure 3.2	The Calculation Process of the Sample Size ..... 117
Figure 4.1	Outputs of the Skewness and Kurtosis Calculations ..... 183
Figure 4.2	Normality of the Error terms for BDAU as Dependent Variables ... 184
Figure 4.3	Normality of the Error terms for FP as Dependent Variables ..... 184
Figure 4.4	Constant variance–Homoscedasticity for the BDAU ..... 185
Figure 4.5	Constant Variance–Homoscedasticity for FP ..... 186
Figure 4.6	Multicollinearity for OR as the Dependent Variable ..... 187
Figure 4.7	Multicollinearity for BDAU as the Dependent Variable ..... 187
Figure 4.8	Interaction Plot of the Effect of Environmental Dynamism on the Relationship between BDAU and Operational Performance ..... 211
Figure 4.9	Interaction Plot of Environmental Dynamism on the Relationship between BDAU and Financial Performance ..... 212
Figure 4.10	Interaction Plot of Absorptive Capacity on the Relationship between BDAU and Operational Performance ..... 213

Figure 4.11 Interaction Plot of Absorptive Capacity on the relationship  
between BDAU and Financial Performance .....213

## LIST OF ABBREVIATIONS

5Vs	Volume, Velocity, Variety, Value, and Veracity
AC	Absorptive capacity
ACC	Acquisition Capacity
ASC	Assimilation Capacity
AVE	Average Variance Extracted
BCa	Bias-Corrected and Accelerated
BDA	Big Data Analysis
BDAU	Big Data Analytics Usage/Use, or the Usage/Use of Big Data Analytics
CB-SEM	Covariance-Based Structural Equation Modelling
CMP	Customer Pressure
CMV	Common Method Variance
COS	Cost
CPA	Compatibility
CPL	Complexity
CPP	Competitive Pressure
CR	Composite Reliability
DCT	Dynamic Capability Theory
DT	Digital Transformation
EB	Expected Benefits
ED	Environmental Dynamics
ERP	Enterprise Resource Planning
EXC	Exploitation Capacity
FP	Financial Performance
FR	Financial Readiness
GDP	Gross Domestic Product
GS	Government Support
HTMT	Heterotrait-Monotrait
IS	Informational Technology

ISC	Insecurity Concern
IT	Information Technology
ITI	IT Infrastructure
MES	Manufacturing Execution System
OP	Organizational Performance
PLM	Product Lifecycle Management
PLS-SEM	Partial Least Squares Structural Equation Modelling
R&D	Research and Development
RBV	Resource-Based View
SC	Supply Chain
SEM	Structural Equation Modelling
SMEs	Small and Medium Enterprises
TAM	Technology Acceptance Model
TMS	Top Management Support
TOE	Technology-Organization-Environment
TRC	Transformation Capacity
VIF	Variance Inflation Factor
VS	Vendor Support

## LIST OF APPENDICES

APPENDIX A	VARIABLE MATRIX OF DBA BASED ON THE TOE FRAMEWORK
APPENDIX B	COVER LETTER
APPENDIX C	QUESTIONNAIRE
APPENDIX D	QUESTIONNAIRE (CHINESE VERSION)
APPENDIX E	PRETEST FEEDBACK RECEIVED AND SOLUTIONS
APPENDIX F	MISSING VALUE ANALYSIS
APPENDIX G	OUTLIERS
APPENDIX H	LINEARITY OF VARIABLES
APPENDIX I	MULTICOLLINEARITY
APPENDIX J	AUTO-CORRELATION

# **PENENTU PENGGUNAAN ANALITIK DATA BESAR DAN KESANNYA TERHADAP PRESTASI DALAM SYARIKAT PEMBUATAN CINA**

## **ABSTRAK**

Industri pembuatan merupakan asas kepada kekuatan sesebuah negara dan tulang belakang kepada ekonomi nasional. Analitik data besar (BDA) kini semakin dianggap sebagai sumber strategik dalam industri pembuatan yang setanding nilainya dengan tanah, emas, dan minyak. Walau bagaimanapun, kebanyakan penyelidikan yang sedia ada lebih tertumpu kepada niat untuk mengadopsi BDA, manakala kurang kajian memberi tumpuan kepada tingkah laku selepas adopsi, iaitu penggunaan BDA (BDAU). Kajian ini merumuskan satu rangka kerja teori yang komprehensif berdasarkan kerangka teknologi-organisasi-persekitaran, pandangan berasaskan sumber, dan teori keupayaan dinamik. Tujuh persoalan dikemukakan untuk mencapai tujuh objektif: menyiasat faktor-faktor anteseden dan hasil BDAU dalam syarikat pembuatan di China serta menilai kesan penyederhanaan kedinamikan persekitaran dan kapasiti penyerapan terhadap hubungan antara BDAU dan prestasi operasi serta kewangan. Kajian ini bersifat kuantitatif dengan menggunakan teknik tinjauan secara keratan rentas dan pensampelan bertujuan untuk mengumpul data daripada 255 syarikat secara dalam talian bagi menguji hipotesis yang dicadangkan. Data dianalisis menggunakan SmartPLS-4, di mana kebolehpercayaan konstruk, kesahan, kesahan konvergen, dan diskriminan bagi semua konstruk memenuhi keperluan ambang statistik. Tiada isu kolineariti dikesan dalam model ini. Hasil kajian menunjukkan bahawa: (1) Sembilan anteseden, iaitu faedah yang dijangkakan, keserasian, kerumitan, sokongan pihak pengurusan tertinggi, infrastruktur IT, kesediaan kewangan, tekanan pelanggan, tekanan persaingan, dan sokongan kerajaan

mempunyai hubungan signifikan dengan BDAU. Sebaliknya, tiga anteseden, iaitu keseimbangan keselamatan, kos, dan sokongan vendor, tidak menunjukkan hubungan yang signifikan dengan BDAU. (2) BDAU memberi kesan positif dan signifikan terhadap prestasi operasi dan kewangan. (3) Prestasi operasi menjadi pengantara sebahagian antara hubungan BDAU dan prestasi kewangan. (4) Kapasiti penyerapan memberikan kesan penyederhanaan positif, manakala kedinamikan persekitaran memberi kesan penyederhanaan negatif terhadap hubungan antara BDAU dengan prestasi operasi dan kewangan. Kajian ini menyumbang dengan menyepadukan kerangka teknologi-organisasi-persekitaran, pandangan berasaskan sumber, dan teori keupayaan dinamik untuk menghasilkan rangka kerja komprehensif yang menghubungkan faktor-faktor anteseden dengan hasil BDAU. Ia turut menambah kepada pengetahuan sedia ada dengan menonjolkan peranan penting kedinamikan persekitaran dan kapasiti penyerapan dalam mempengaruhi tingkah laku syarikat terhadap BDAU. Kajian ini memberi pandangan baharu untuk membantu syarikat pembuatan memahami faktor-faktor anteseden dan hasil BDAU serta cara memanfaatkan kedinamikan persekitaran dan kapasiti penyerapan untuk meningkatkan prestasi operasi dan kewangan. Kajian ini turut memberikan panduan kepada vendor BDA untuk memahami faktor positif, negatif, dan tidak signifikan dalam penggunaan BDA supaya mereka dapat membangunkan produk BDA yang lebih baik untuk memenuhi keperluan pelanggan. Selain itu, kajian ini memberi panduan kepada pihak kerajaan dalam merangka dasar bagi menggalakkan pembangunan BDA dalam kalangan syarikat pembuatan di Cina.

# **DETERMINANTS OF BIG DATA ANALYTICS USAGE AND ITS IMPACT ON PERFORMANCE IN CHINESE MANUFACTURING COMPANIES**

## **ABSTRACT**

Manufacturing is the foundation of a country and the basis of a strong country, and it is the lifeline of the national economy. Big data analytics (BDA) is increasingly viewed in the manufacturing industry as strategic resources that are comparable in value, such as land, gold, and oil. However, most of the existing research has focused on BDA adoption intentions, while a lack of research has focused on postadoption behaviors, that is, BDA usage (BDAU). This study formulated a comprehensive theoretical framework based on the technological-organizational-environment framework, the resource-based view, and dynamic capabilities theory. Seven questions were proposed to achieve seven objectives: investigating the antecedents and outcomes of BDAU in Chinese manufacturing companies and evaluating the moderating effects of the environmental dynamic and absorptive capacity between BDAU and operational and financial performance. This study is quantitative and uses cross-sectional survey and purposive sampling techniques to collect data from 255 companies online to test the proposed hypotheses. The data were analysed via SmartPLS 4, and the construct reliability, validity, and convergent and discriminant validity of all the constructs met the statistical threshold requirements. Collinearity was not a problem in this model. The results show that (1) nine antecedents (expected benefits, compatibility, complexity, top management support, IT infrastructure, financial readiness, customer pressure, competitive pressure, and government support) have a significant relationship with BDAU, whereas three antecedents (insecurity concerns, cost, and vendor support) have no

significant relationship with BDAU. (2) BDAU has a positive significant effect on operational and financial performance. (3) Operational performance partially mediates the relationship between BDAU and financial performance. (4) Absorptive capacity has a positive moderating effect, whereas environmental dynamics have a negative moderating effect on the relationship between BDAU and operational and financial performance. This study provides a comprehensive framework by integrating the technological-organizational-environment framework, the resource-based view, and dynamic capabilities theory and expands upon the existing knowledge by developing a bridge between the antecedent factors and the outcomes of BDAU. This study also enhances the existing body of knowledge by highlighting the importance of environmental dynamism and absorptive capacity in influencing a company's behaviour towards BDAU. This study is a step toward responding to the call of prior studies and addresses the limitations of prior studies by scholars, which is a noticeable contribution to the literature on BDAU. This study provides novel insights to help manufacturing companies understand the antecedents and outcomes of BDAU and how to leverage environmental dynamism and absorptive capacity to improve their operational and financial performance. This study also assists BDA vendors in understanding the positive, negative, and insignificant factors in using BDA so that they can develop better BDA production that meets customer needs. This study also provides guidance for the government in formulating policies to promote the development of BDA among Chinese manufacturing companies.

# **CHAPTER 1**

## **INTRODUCTION**

### **1.1 Introduction**

At the beginning of this study, the research background is first introduced, and the importance of this study is highlighted. This was followed by the research problems. The third is to focus on the research objectives and questions. The fourth is to position the study and limit its scope. Fifth, the significance of this study is emphasized. The operationalization of key terms was then defined. Finally, the structure of the proposal was designed. This chapter laid the foundation for the full text.

### **1.2 Background of the Study**

This section explains the background of this study from the macro to the micro level, including the increasing digital economy, the importance of big data and big data analytics (BDA), the importance of big data, and BDA in Chinese manufacturing.

#### **1.2.1 The Importance of Manufacturing in the Economy and Society**

Manufacturing is the production of products using raw materials, machines, workers, and tools (Ferdows & De Meyer, 1990). The manufacturing industry includes activities where laborers use tools and machines to convert raw materials to final products, transfer products from manufacturers to vendors, and recycle used goods (Zhong et al., 2016). Manufacturing is the foundation of a country and the basis of a strong country, and it is the lifeline of the national economy. According to the national economic statistical classification, China's manufacturing industry has 31 major categories, 179 medium categories and 609 small categories, making it the

manufacturing industry with the most complete industrial categories and the most complete industrial system in the world.

The manufacturing industry is growing rapidly. According to data from the Tanji Big Data Research Institute, the number of newly registered manufacturing companies in China steadily increased over the 10 years from 2014--2023 (Figure 1.1). The number of newly registered companies in 2014 was 952,000, and the number of newly registered companies in 2023 reached 1.662 million, which nearly doubled in 2014. The total base of companies is very large (Tanji, 2024).

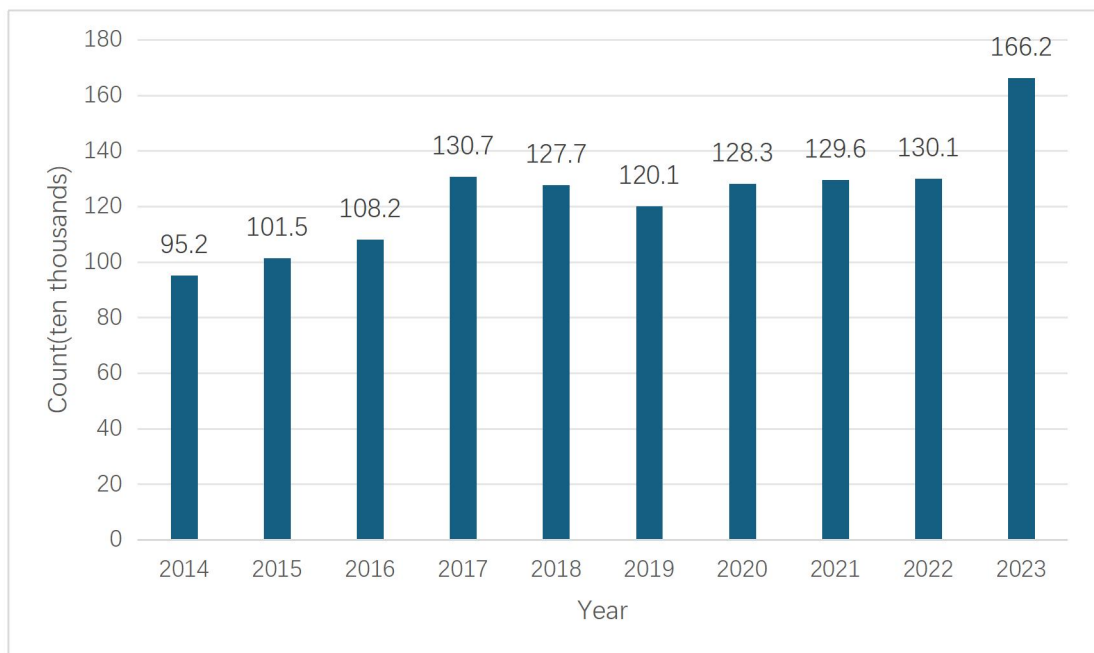


Figure 1.1 Number of Registered Manufacturing Companies in the Last 10 Years  
The manufacturing industry has made important contributions to the

development of China's economy and society. For example, in 2023, first, China's manufacturing value added accounts for approximately 27% of the country's GDP, while the total industrial value added is approximately ¥39.91 trillion, a year-over-year increase of 4.2% (NBS, 2024). In particular, the revenue of China's high-end manufacturing listed companies will increase from ¥8.24 trillion in 2019 to ¥14.66 trillion in 2023, with a compound growth rate of 15.50%, and the income growth rate

will be significantly higher than the GDP growth rate. Second, the tax contribution of China's high-end manufacturing listed companies reached ¥243.562 billion, with a compound growth rate of 13.24% over the past five years, making important contributions to society. Third, the number of employees reached 9.8059 million, with a compound growth rate of 13.24% over the past five years. A total of 10.74% provide many jobs for society and absorb a large amount of technical talent. Finally, the R&D expenditure of listed companies in the high-end manufacturing industry reached ¥888.218 billion, with a compound growth rate of 22.11% in the past five years. The annual growth rate has remained high. R&D investment continues to increase rapidly, indicating that China's high-end manufacturing industry attaches great importance to technological progress and industry upgrades (SIAC, 2024).

### **1.2.2 The Importance of BDA in Manufacturing**

With new big data technologies growing at an exponential rate in the last few years (Pereira et al., 2022; Talaoui et al., 2023), BDA has become one of the most important general-purpose technologies (Conti et al., 2024), which involves two main concepts: big data and data analytics (Belhadi et al., 2019). Many companies transform BDA into insight and then action (Ghasemaghahi, 2020a), which has led to a myriad of major changes in both business and society (Van Veldhoven & Vanthienen, 2022; Wysokińska, 2021). Big data can help companies identify customer needs, improve productivity, and gain a competitive advantage (Can & Alatas, 2017) and can improve their ability to develop resources, increase operational efficiency, produce individually tailored goods and services, provide better living experiences, and create many opportunities (Lei et al., 2018).

The value of BDA for making decisions on the basis of data is increasing (Desgourdes & Ram, 2024). BDA enables increasing operational efficiency;

enhancing strategic directions; developing better customer service; and identifying and developing new products, services, customers, and markets (Gangwar, 2018), which is essential for maintaining market competitiveness and staying at the forefront of technological innovation (Feliciano-Cestero et al., 2023). Big data are a driver of business improvements in companies, communication, products and services, and business models, which include business management and customer experience. Big data promises organizations to create business advantages in terms of better decision-making, yielding new insights, cost savings, optimizing business processes, and improving product and service quality (Shah et al., 2017). Companies have embraced BDA to obtain advantages such as enhanced profitability, accurate client demand prediction, cost-effective product development, and enhanced inventory management (Willetts & Atkins, 2024).

With the progress of business activities, the manufacturing industry has generated a large amount of daily data (Gantz & Reinsel, 2011). This large dataset is so complex that it is risky to manage via traditional processing systems (Zhong et al., 2016). Cui et al. (2020) showed that big data can be integrated with software and systems to provide timely information for analytics and innovative applications such as prediction, optimization, monitoring, simulation, and visualization. The industrial sector is currently undergoing a substantial shift as Industry 5.0 emerges (Li et al., 2024).

Six key drivers of big data in manufacturing are system integration, data, prediction, sustainability, resource sharing, and hardware. The nine essential components of big data are data ingestion, storage, computing, analytics, visualization, management, workflow, infrastructure, and security (Cui et al., 2020). With real-time data analytics and information sharing, the application of big data

provides important feedback insights for managers to monitor outputs, reveal operations and diagnose problems (Dubey et al., 2019a; Fatorachian & Kazemi, 2020). By incorporating richer and more timely business operational insights into decision-making, a company can improve its manufacturing and operation processes to avoid expensive and inefficient actions, eliminate accidents and defects, and reduce unnecessary waste and byproducts. These benefits enable companies to reduce operating costs, stabilize the utilization of equipment and improve the quality and productivity of the processes. In addition, big data utilization enables companies to shift flexibly between different offerings and their volumes, which has been deemed an important factor in improving customer satisfaction. The improvement of product and service quality as well as the enhancement of consumer satisfaction led to more value being produced. A company can utilize big data to optimize its value creation by reducing operating costs or improving product delivery (Xiaobo et al., 2022).

Given the different life cycles of big data, manufacturing companies can monitor the production process, promote the coordination of various departments, and predict precise demand, thereby achieving the transformation and upgrading of the manufacturing industry. Furthermore, big data can add characteristics such as self-learning, self-execution, and self-regulation to the manufacturing process (Tao et al., 2018). With the accelerated integration of IT with manufacturing systems and the increasing richness of the data owned by companies, including volume, variety, and velocity (Gao et al., 2020), the operation of manufacturing systems will greatly change with the further development of BDA, and applications in product design, planning and scheduling, quality optimization, equipment operation, and maintenance will be carried out to substantialize intelligent manufacturing systems

(Wang et al., 2022). The trend of servitization further requires manufacturing companies to use big data to capture customers' needs (Xu et al., 2023).

Currently, manufacturing processes are increasingly operating in uncertain and complex environments with complex operations and complex constraints (Cheng et al., 2018). The utilization of BDA in predictive maintenance has great potential for optimizing maintenance plans and minimizing unplanned downtime in manufacturing plants (Sharma & Gurung, 2024). The vast need for real-time, dynamic, fault identification and self-adaptive, accurate production management has created new challenges for traditional technology (Belhadi et al., 2019). Organizations that are able to monitor their operations through the fast-paced increasing amount of data to forecast their quality fault and proactively control their processes by means of advanced analytics will be in advance of their competitors (Krumeich et al., 2016). BDA holds enormous potential for improving quality and process control, energy and environment efficiency, proactive diagnosis and maintenance, safety, and risk analysis (Belhadi et al., 2019). BDA in manufacturing is expected to facilitate and improve business process monitoring and has become a catalyst for improving supply chain management, enriching industrial automation, and accelerating business innovation (Maroufkhani et al., 2019).

The application of BDA can help in making informed decisions such as better forecasts for products, performance management across multiple manufacturing units, improving the quality of products and services, providing greater visibility to operations, understanding customer preferences and buying patterns, real-time manufacturing processes and asset condition monitoring, product design, and customer service (Shukla et al., 2019). Several companies in the manufacturing industry have started utilizing BDA to obtain a competitive advantage (Bülent et al.,

2024; Maia et al., 2024). BDA provides insights that can greatly improve product innovation capabilities (Bülent et al., 2024) and help companies make more informed business decisions, particularly by revealing hidden patterns, unknown correlations, market trends, customer preferences, and other useful information (Gandomi et al., 2022). On the basis of the above discussion, to keep pace with a changing marketplace, it is more important for manufacturing companies to use BDA than ever before.

BDA can solve complex business problems across multiple domains, such as operations, finance, marketing, strategy governance, security, and managerial decision-making (Ogbeide et al., 2020), and measure risks, opportunities, predictive analysis measures, demand forecasting, optimization, inventory and resource planning, market segmentation, customer modelling, etc. (Sen et al., 2016). BDA can also optimize prices, increase profit, and maximize sales, financial productivity, market share, and return on investment (Maroufkhani et al., 2019). Many companies use BDA to improve their products and services and support smart decision-making to gain a competitive advantage (Maroufkhani et al., 2019; Yan et al., 2024).

Big data promotes the understanding of customers' behaviours, interactions, and experiences; a better understanding of customers and markets facilitates innovation by providing more insights for customization. In addition, big data help companies discover new customers, and markets can exert disruptive power over traditional business models and help to develop new revenue streams, which leads to business model innovation (Ritter & Pedersen, 2020). As big data competency increases the connectivity and complementarity among intracompanies and further intercompany entities and companies shift from optimizing extant businesses or fields to pioneering new ones, stakeholders, including customers, suppliers, partners,

and incumbents in the targeted fields, are connected and participate in the value creation of companies (Xiaobo et al., 2022). Therefore, big data profoundly impacts business models, as it will reconceive interactions among consumers, businesses, and suppliers (Feliciano-Cestero et al., 2023).

Table 1.1 Summary of the Role of BDA

Roles	Describes
Improving production efficiency	By analysing a large amount of data in the production process in real time, manufacturing companies can control the production process more accurately and reduce the probability of human errors and machine failures. In addition, BDA can collect and analyse equipment operation data, identify potential failure modes in advance, and help companies perform maintenance before equipment failures occur, significantly reducing unplanned downtime of equipment, extending equipment service life, reducing maintenance costs, and improving production efficiency (Lee et al., 2015; Van Dinter et al., 2022).
Improving product quality	BDA can help companies monitor and analyse key parameters in the production process (such as temperature, pressure, humidity, etc.), to detect anomalies early and avoid product quality problems. Through big data analysis, companies can also identify key factors that affect product quality and continuously improve product design and process flow (Wang et al., 2022).
Optimizing Supply Chain	BDA helps manufacturing companies optimize supply chain management by analysing orders, inventory, logistics and other information in the supply chain in real time. Through more accurate demand forecasting and inventory management, manufacturers can effectively reduce inventory costs, reduce material waste, and quickly respond to changes in market demand (Anh & Cheng, 2020).
Reducing operating costs	Through big data analysis, companies can analyse various consumption data in the production process, optimize the use of energy and raw materials, and thus reduce production costs. In addition, data-based decision optimization can also help companies discover and

	reduce unnecessary links or processes, thereby improving overall operational efficiency (Wang et al., 2016).
Quickly responding to market changes	With the help of big data analysis, the manufacturing industry can analyse the personalized needs of consumers, quickly design and manufacture products that meet the needs of different customers, and realize flexible manufacturing and mass customization. This enables manufacturing companies to quickly respond to market changes and meet the diverse needs of consumers (Dubey et al., 2018).

According to the “2022 Digital Transformation Market Trends Report,” 78% of survey respondents felt that digital transformation (DT) is imperative for a company’s survival, with 24% regarding DT as their top priority. The International Data Corporation (IDC), a technology market research organization, predicts that 40% of the total revenue for G2000 organizations by 2026 will be generated by digital products, services, and experiences, and 90% of organizations that accurately quantify the value of their digital capabilities and assets will significantly improve their market valuation and competitive position (IDC, 2023). Another study by the IDC shows that by 2024, more than half of the global economy will be based on or influenced by digitalization, and more than 90% of businesses and organizations will make DTs the centrepiece of their growth strategy (Yu & Yan, 2022). According to the Fortune Business Insights report, the global DT market size is \$1.79 trillion in 2022 and is projected to increase to \$6.78 trillion by 2029, with a CAGR of 20.9% during the forecast period (FBI, 2023). By 2025, 75% of Fortune’s top 500 global companies are expected to promote organizational changes through DT (Oh et al., 2022). DT has been shown to positively impact market players’ formation, communication, transaction costs, and performance, among other aspects (He et al., 2024). It is likely that companies fail if they cannot adapt to the new digital reality, become victims of "digital Darwinism" and may disappear. Only those companies that are more adaptable and responsive to technological trends will survive and remain in this new competitive landscape (Wysokińska, 2021).

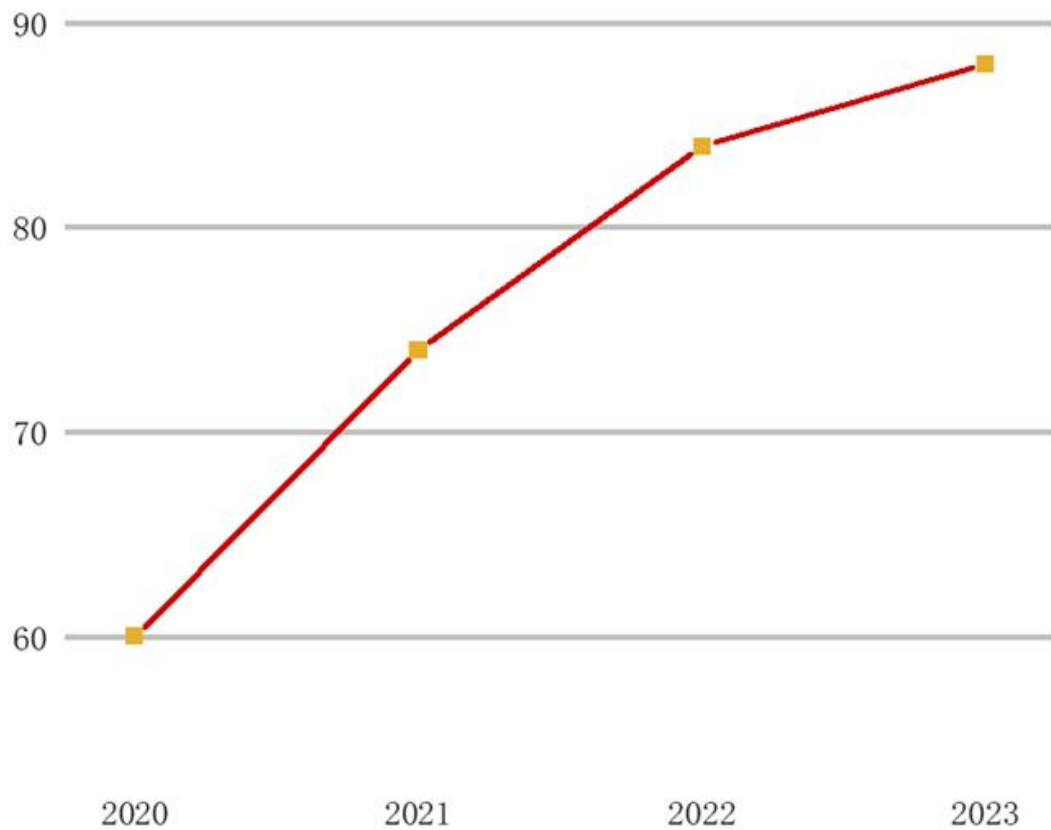


Figure 1.2 Trends in China's Manufacturing Digital Transformation Index

### 1.2.3 The Current State of the BDA in Chinese Manufacturing

In the Outline of the 14th Five-Year Plan, the Chinese government proposed driving the reform of the production mode and the lifestyle and governance mode through digital transformation. In 2020, the National Development and Reform Commission of China proposed the initiative of The DT of Partnership. In 2022, China's Government Work Report proposed that digital development should be accelerated, new advantages of the digital economy should be created, and digital industrialization and industrial DT should be promoted together, which shows that DT has risen from the company level to the national level (Feng et al., 2022). Manufacturing companies above the scale will have fully popularized digitalization, and major companies will have realized transformation. Manufacturing companies have also responded to advocacy to actively participate in DT (Zhao et al., 2023).

According to the 2023 V1 Global Big Data Spending Guide report, the overall IT investment in China's big data market will be approximately \$17 billion in 2022 and is expected to double to \$36.49 billion in 2026. Compared with the global total, the Chinese market will continue to increase its share in the five-year forecast period and is expected to be close to 8% of the global total in 2026 (Goepfert et al., 2023). China's big data industry grew by almost 18% in 2022 compared with the previous year, exceeding a market size of ¥1.5 trillion (Slotta, 2024).

Owing to the manufacturing industry facing multiple challenges, such as the ever-changing market environment, diversified customer demands, and intensified homogeneous competition, many companies have chosen to adapt to the wave of technological change driven by goals such as quality, efficiency, and cost. According to data from the National Bureau of Statistics, in 2023, investment in technological transformation in the manufacturing industry increased by 3.8%, and investment in high-tech industries increased by 10.3%, which is faster than the growth rate of all fixed asset investment. New technologies such as big data and BDA promote high-quality development in all aspects of the manufacturing industry (Tanji, 2024). As the digitalization process of the manufacturing industry accelerated, data from the Tanji Big Data Research Institute showed that in the seven years from 2017--2023, except for the impact of the epidemic in 2020, the demand for jobs related to the digital transformation of the manufacturing industry continued to grow. Digital transformation promotes the establishment of new production factors, R&D paradigms, and business models, bringing unprecedented value to the manufacturing industry. Digitalization is reshaping the future of the manufacturing industry. This transformation process is not only a subversion of the original supply chain system but also affects all subindustries of the manufacturing industry and every link in the

industrial chain value chain. The core of this transformation is to reduce costs, improve efficiency, and stimulate new business models, providing new possibilities for many fields to stabilize development momentum with higher efficiency (Tanji, 2024).

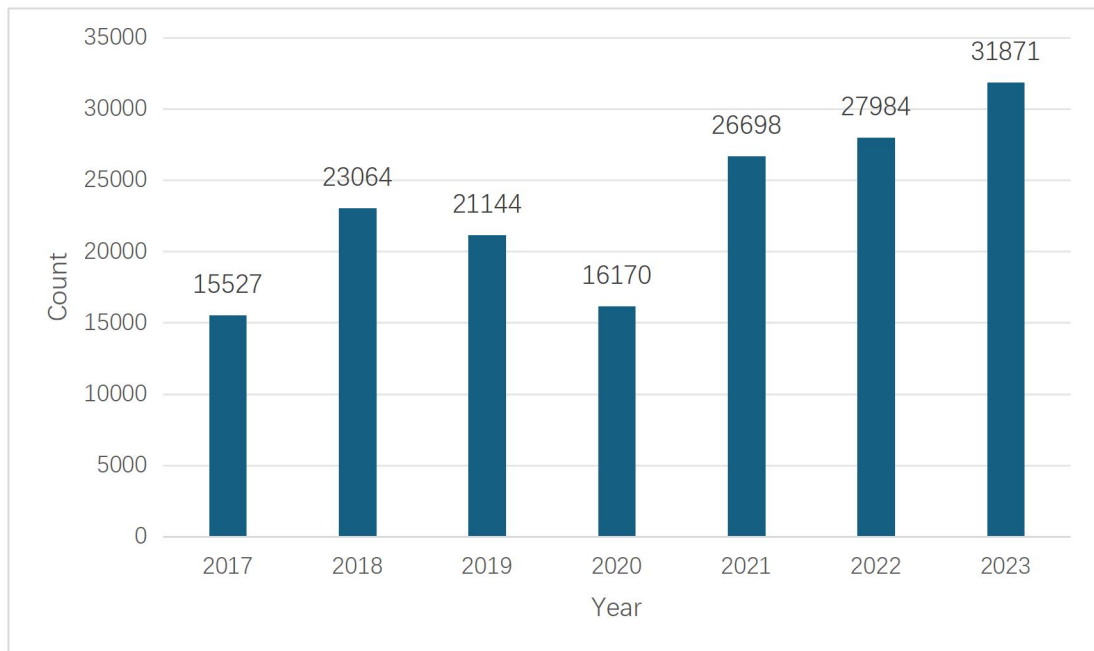


Figure 1.3 Number of Companies Recruiting for Digitally Related Positions

The digital transformation of China's manufacturing industry has entered a period of rapid development in which the scope has significantly expanded, the degree has continuously increased, and the quality has greatly improved. With the continuous advancement of digital technology and the continuous expansion of application scenarios, the manufacturing industry will achieve higher quality, higher efficiency, and more sustainable development goals. At the same time, the digital transformation of the manufacturing industry will also inject strong momentum into the development of a modern industrial system and achieve high-quality economic development. In 2023, the scale of China's digital economy exceeded ¥55 trillion, accounting for approximately 10% of GDP and becoming an important engine of economic growth (SIAC, 2024).

## **1.3 Problem Statements**

### **1.3.1 Lack of Competitiveness for China's Manufacturing Industry**

First, although China's manufacturing industry is large in scale and has a sound system and a complete range of products, some subsectors are still at the middle and low ends of the global value chain, with low product added value, and some high-end industries lack core technology and international competitiveness. In particular, companies cater mainly to customer business needs, with serious product homogeneity, low added value and insufficient competitiveness (Tanji, 2024). For example, there is a lack of authoritative data standards, and the level of data openness and sharing is not high (SIAC, 2024).

Second, China's manufacturing industry is facing increasing resource constraints (such as land, labor, and energy), which has led to rising factor costs and squeezed the profit margins of enterprises. This challenge particularly affects traditional manufacturing industries, and their transformation and upgrading needs have become more urgent (Peng, 2024). Financial performance is one of the important outcomes of BDAU (Thanabalan et al., 2024). However, according to the 2024 China Manufacturing Development Trend Report, owing to the impact of global pandemics such as the COVID-19 pandemic, Chinese manufacturing companies are generally facing the dilemma of rising costs and declining demand, which has had a certain impact on the financial performance of manufacturing companies. Furthermore, owing to the lack of good financial performance in the past 10 years, the number of Chinese manufacturing companies that have been deregistered has been gradually increasing (see Figure 1.4), reaching a peak in 2023, and the industry has entered a period of transformation and adjustment (Tanji, 2024).

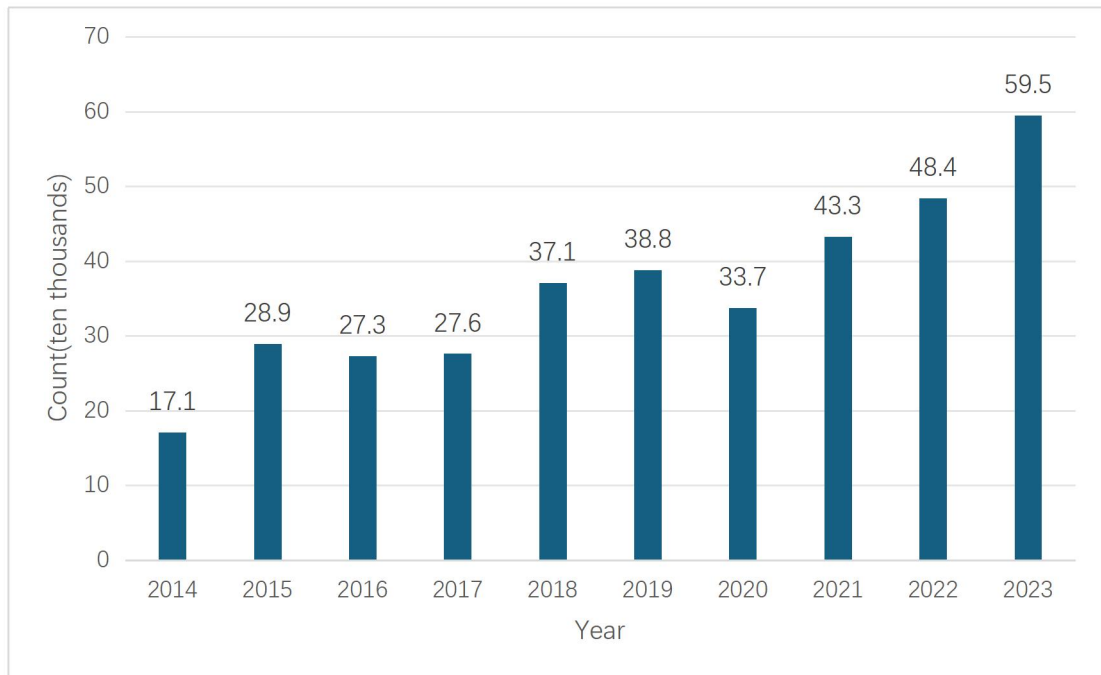


Figure 1.4 Number of Manufacturing Companies Deregistered in the Past 10 Years  
 Third, although the Chinese government has vigorously promoted the digital transformation of the manufacturing industry, many companies are still slow in progressing through smart manufacturing and digital upgrading, and their digital transformation is insufficient (Du, 2024).

Fourth, owing to intensified international competition, especially in the field of high-end manufacturing, China is competing strongly with Europe, the United States, Japan, South Korea and other countries in the international market. Moreover, the low-end manufacturing industry is impacted by other developing countries, resulting in increased export pressure and intensified competition in China's manufacturing industry (NIF, 2021). Therefore, China's manufacturing industry is also facing the dual pressure of some developed countries promoting the return of high-end manufacturing and emerging countries relying on their labor cost advantages to absorb the relocation of low-end manufacturing (SIAC, 2024).

Finally, in the industrial sector, BDAU improves operational performance. For example, the BDA improved production efficiency to 21%, the weaving process improved to 23%, and the overall process improved to 17.06% (Saad et al., 2021). Manufacturers need to deal with an average of 800 hours of downtime each year, which means that productivity losses increase from 5% to 20%. However, General Electric has managed to automate its manufacturing processes, optimize performance, and eliminate downtime by predicting when a machine or component will fail through big data analysis, thereby gaining \$45 billion in market revenue each year (looker, 2020). BDA is no longer an option if companies are to thrive in the changing digital environment in China, the largest digital market, rather than the courage to innovate and change entire business operations to improve operational performance (Zha, 2017), but a 2017 Accenture report revealed that only 4% of China's manufacturing companies achieved both digital and financial performance (Zha, 2017), whereas a majority (58%) achieved neither strong digital operation nor outstanding financial performance (Zha, 2017). BDAU can increase operating margins by up to 60% and reduce expenditures by 8%, highlighting its role in streamlining operations and enhancing efficiency (Ertz et al., 2024).

Faced with these problems, manufacturing companies hope to improve their operational and financial performance by using BDA. The BDA of manufacturing companies plays a key role in reducing costs and risks, improving production efficiency, optimizing management processes, and innovating services and business models (Liu et al., 2024).

### **1.3.2 Lack of Research on Big Data Analytics Usage (BDAU)**

BDA is a science and technology that involves analysing and discovering knowledge, patterns, relationships, and valuable intelligence from big data;

visualizing and reporting the discovered knowledge to obtain insights; and assisting decision-making. It processes and analyses big data through the comprehensive application of advanced analytics methods, procedures, tools, and infrastructure (Belhadi et al., 2019; Chong & Shi, 2015; Huynh et al., 2023; Jaber & Abbad, 2021; Ji-fan Ren et al., 2016; Naeem et al., 2022). As a closely related concept, BDAU refers to the use of BDA to achieve support value creation and optimize business performance (Belhadi et al., 2019; Chong & Shi, 2015; Huynh et al., 2023; Jaber & Abbad, 2021; Ji-fan Ren et al., 2016; Naeem et al., 2022); BDAU reduces uncertainty by stimulating insights and knowledge creation and increases organizational capability for strategic decision making (Chen et al., 2015). There is currently high fragmentation and low generalizability in the BDAU literature (Williams et al., 2019). A recent study by Kumar (2023) revealed a lack of comprehensive and exhaustive investigations on BDAU in the literature. Huifen and Jifan (2018) noted that most of the prior BDA research in the business and management field has focused on adoption intentions, but there is a lack of research focused on postadoption behaviors (that is, BDAU), and research on BDAU is lacking. Gupta et al. (2020) reported that many existing studies have examined the factors involved in the initial adoption of digital technologies, but there has been a limited focus on postadoption behaviours. Although a focus on BDA adoption is helpful for understanding adoption decisions, investigating BDA adoption or initial use does not guarantee the identification of success factors for BDA implementation in an organization (Javdan & Ghasemaghaei, 2021). BDAU still requires a better understanding of postadoption variations in actual usage and the outcome of actual usage. There is a lack of empirical evidence to gauge BDAU and its impact on company performance, partly because it is difficult to develop measures and collect

data (Zhu & Kraemer, 2005). Chen et al. (2015) developed a measure of BDAU, which led to the adoption and discussion of some later researchers to further demonstrate the theoretical model, laying a good foundation for this study. In addition, enhancing companies' business processes to maintain sustainable competitive advantage is an ongoing activity, and postimplementation phases are critical (Ruivo et al., 2014). Overall, the literature reviewing BDAU is still very limited (Sivarajah et al., 2024). These gaps in the literature limit the understanding of the antecedents and outcomes of BDAU, and this study sought to narrow these gaps.

A complex and crucial question confronting managers in virtually all of today's companies concerns whether, when, and how to innovate with information technology (Raguseo & Vitari, 2018b). Many companies still do not know if the benefits of BDAU outweigh its challenges and costs (Ghasemaghaci, 2020a), and many companies attempt to use big data and BDA to capture and profit from the enormous amount of data available from various sources (Raguseo & Vitari, 2018b). Therefore, it is necessary to understand the most critical antecedent factors and outcomes of the BDAU to determine how to support decision-making for the BDAU and to better leverage it to achieve a competitive advantage. Huifen and Jifan (2018) highlighted that there are too few antecedent factors influencing BDAU in the prior literature, which may lead to a few problems in which many organizations still seem to be at the stage of understanding big data value, the necessity of IT and analytical skills, the risks involved, and how to provide compelling business cases for a substantial amount of investment necessary.

This study attempts to address several limitations and calls of previous researchers for BDAU. First, in the technology dimension, expected benefits and compatibility are positive influencing factors for BDA (Al-Dmour et al., 2023;

Maroufkhani et al., 2023). Complexity (Maroufkhani et al., 2023), insecurity concerns (Ghasemaghahi, 2020a), and cost (Wong et al., 2020) are negative influencing factors of BDA. Clearly, it is not enough to focus on the positive factors influencing BDA. Therefore, this study not only considers the positive factors influencing BDA but also focuses on complexity, insecurity concerns, and cost as negative factors influencing BDA. Several issues in the BDAU, such as data security and privacy, crisis and risk management, and costs, also arise (Belhadi et al., 2019). The number of companies that intend to invest in BDA has declined, and those that invest in BDA cannot successfully deploy their projects for production (Ghasemaghahi, 2020a). Chen et al. (2015) reviewed the influencing factors of BDAU in the three dimensions of technology, organization, and the environment. However, each dimension contains very few factors (including 2 technological factors, 2 organizational factors, and 1 environmental factor). In addition, it has been 8 years, and the technology and environment have changed greatly. Whether their conclusions are applicable in the current technology and environment context should be checked. Huifen and Jifan (2018) acknowledged the limitations of their research in that there are few antecedent factors. Their study included only four antecedent factors, namely, perceived usefulness, satisfaction level with existing IT technology, competitive pressure, and technology compatibility. Ghasemaghahi (2019) highlighted the limitations of their research on BDAU, which they assessed the important role of both structural and psychological readiness in obtaining value from BDAU; however, they also indicated that BDAU may be affected by factors other than the factors considered in their study and suggested that future studies investigate the impact of other variables on BDAU. Yeh (2023) encouraged future research to examine BDAU with nuanced insights. Cheng and Lu (2018b); Li et al. (2022); Wei

et al. (2022) used BDAU as the independent variable and did not examine its antecedent factors. This study responds to Chen et al. (2015); Huifen and Jifan (2018); Clarke (2016) calls and should consider more dimensions and antecedents of BDAU in the future by examining the antecedent factors of BDAU from the perspective of technology, organization, and environment dimensions.

Second, the depth of research on the organizational factors of DBAU is insufficient. As shown in Appendix A, top management support was fully demonstrated as an organizational factor of BDA, appearing 16 times in 24 articles, accounting for 66.7%. In fact, another organizational factor that received more attention was organizational readiness, which appeared 9 times, accounting for 37.5%. However, other factors, such as IT infrastructure, financial readiness, business strategy, financial resource slack, absorptive capability, company size, vision and strategy, sponsorship and governance, organizational structure, talent strategy and capability, organizational data environment, industry type, skills and experience, IT expertise, organizational resources, and financial investment capability, have not been investigated more than 5 times. In existing research, organizational readiness involves IT infrastructure, financial resources, analytics capability, and skilled resources. Big data is a driver of business success across a wide range of industries, and organisations are investing considerable resources in big data initiatives to improve company performance. However, big data is not a panacea; ‘an uncritical analysis of poorly understood datasets does not generate knowledge’, and large investments could ruin companies (Raguseo & Vitari, 2018b). To further discuss organizational factors, this study takes IT infrastructure and financial readiness as independent variables.

Similarly, among the environmental factors influencing BDA in Appendix A, competitive pressure and government support were discussed more often, appearing 16 times and 13 times, respectively, accounting for 66.7% and 54.2%, respectively. However, the impact of vendors and customers as the same stakeholders of the company is less discussed, especially since customer pressure appears only once, which highlights the lack of theoretical guidance on the impact of customers on DBA. This study considers the influence of competitors, the government, vendors, and customers from the perspective of company stakeholders, which are closely related to business activities in company BDAU. This study fills the gap that vendors and customers lack theoretical guidance on BDAU.

Despite the increasing pervasiveness of BDA across industries, previous studies have not fully investigated how BDA benefits actually materialize (Conti et al., 2024). However, very few organizations measure the benefits of BDAU (Conti et al., 2023; Jensen et al., 2023). Huifen and Jifan (2018) considered operational performance the main aspect of organizational performance. However, different studies have shown different results, so there is still no common view. Huifen and Jifan (2018) also recommended that future research examine the different outcomes of company performance when companies begin using BDA at different times. Cheng and Lu (2018a) suggested that future studies explore further whether alternative constructs affect BDAU and organizational performance. Chen et al. (2015) recommended that future research examine the influence of the company-level employment of BDAU on other aspects of organizational performance beyond the finite components examined in the existing study. Sivarajah et al. (2024) showed that BDA has a substantial effect on company performance, but they did not examine

the impact of BDA on different dimensions of company performance, such as operational and financial performance.

Therefore, this study attempts to address some limitations of previous studies and responds to their research suggestions to further supplement and improve the theoretical basis of BDAU. Specifically, this study investigates 12 antecedents of BDAU and its influence on operational and financial performance.

### **1.3.3 Different Internal and External Environments have Different Effects on Company Performance**

On the one hand, because a company's external environment is characterized by instability and volatility (Schilke, 2014), although the advantages of BDA are dependent upon the nature of the company's practices, the environment under which these capabilities are utilized also plays a key role in making them either more effective or ineffective (Prashar & Gupta, 2021). For example, environmental dynamism determines how quickly products become obsolete (Rodríguez-Peña, 2021), the strategic moves of competitors cannot be easily foreseen (Charoensukmongkol, 2022), and a surge of dynamism negatively affects the performance of these companies (Dogru et al., 2019; Onngam & Charoensukmongkol, 2023, 2024). For example, according to official data on industrial output released by the National Bureau of Statistics of China, many industries have been hit hardest by the epidemic and the ensuing lockdown (Richter, 2020). In particular, the value added in motor vehicle manufacturing was 31.8% lower than that in the same period of the previous year. Figure 1.5 provides an overview of output declines across all major manufacturing sectors.

Wamba et al. (2020) highlighted that the effects of BDA on cost performance and operational performance were greater under intermediate levels of environmental

dynamism but were comparatively weak when environmental dynamism was low or high; that is, a nonlinear, inverse U-shaped moderating effect of environmental dynamism existed. Wei et al. (2022) suggested that the value of the BDA may be affected by environmental volatility, and further research should consider the impact of environmental factors between BDAU and organizations. Chen et al. (2015) suggested that future research replicate their study on the differential effects of environmental volatility on internal and external performance to assess whether such differential effects of environment dynamism would hold when different performance metrics are used. Maroufkhani et al. (2019) noted that empirical research focusing on the value of the BDA is still insufficient. Chen et al. (2015) asserted that their study on BDAU as an organizational asset is in the early stages of development, and it would be interesting to evaluate BDAU when this phenomenon becomes more mature. They call for additional insight into the temporal nature of the way BDAU influences aspects of organizational performance, specifically through the interplay of the dynamic environment. Therefore, this study adopts the suggestion of Chen et al. (2015) and considers environmental dynamism as a moderating variable to examine the differential effects of environmental volatility on operational and financial performance.

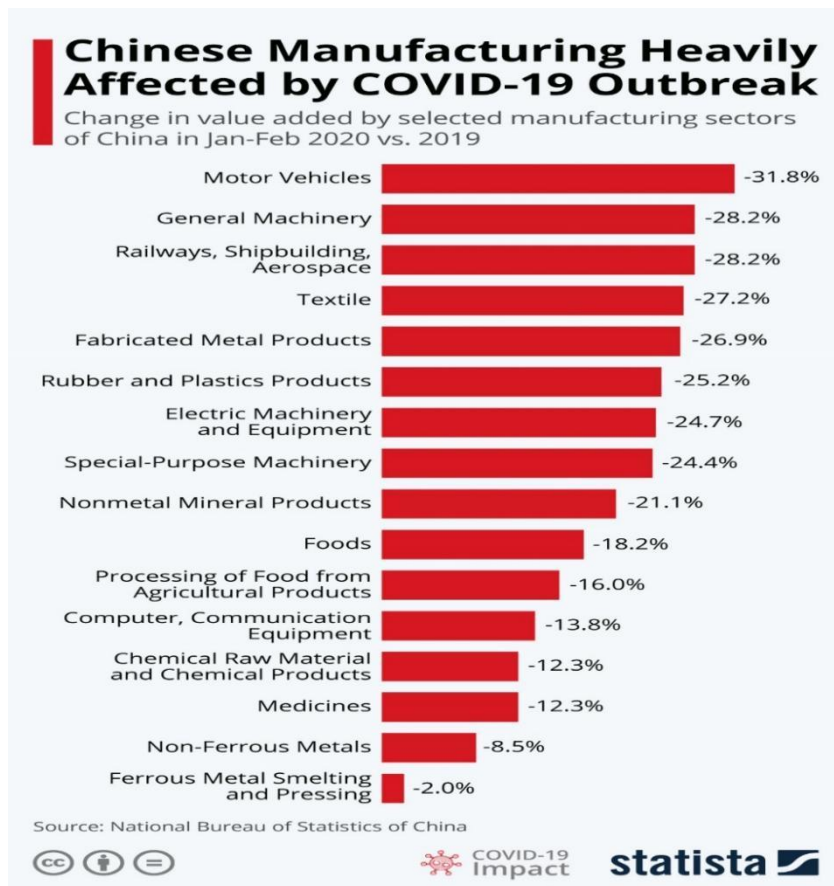


Figure 1.5 Chinese Manufacturing Heavily Affected by the COVID-19 Outbreak

On the other hand, the ability of a company to use existing internal knowledge to acquire, assimilate, transform, and develop external knowledge is considered an important internal capability of the company (Zahra & George, 2002). Absorptive capacity is an important internal capability of a company and plays an important role in new information and knowledge generation (Blanco et al., 2018). However, few articles have mentioned the importance of absorptive capacity in the relationship between BDA and company performance (Maroufkhani et al., 2019). Insights to help decision-making can be generated from BDA through acquisition and assimilation capabilities. The insights can be transformed into new knowledge to be applied and exploited to improve products and processes, and the insights can also serve as input for the generation of new ideas and the strengthening of the knowledge inventory that can potentially be developed and implemented (Lozada et al., 2023).