CORA Cork Open Research Archive
Cartlann Taighde Oscailte Chorcaí

Title	Democratising data governance: theorising workaround-centric data activities as patterns of action
Authors	Wibisono, Arif
Publication date	2023
Original Citation	Wibisono, A. 2023. Democratising data governance: theorising workaround-centric data activities as patterns of action. PhD Thesis, University College Cork.
Type of publication	Doctoral thesis
Rights	© 2023, Arif Wibisono. - https://creativecommons.org/licenses/by-nc-nd/4.0/
Download date	2026-10-29 02:32:06
Item downloaded from	https://hdl.handle.net/10468/14484

UCC
University College Cork, Ireland
Coláiste na hOllscoile Corcaigh

Ollscoil na hÉireann, Corcaigh

National University of Ireland, Cork

Democratising Data Governance: Theorising Workaround-Centric Data Activities as Patterns of Action

Thesis presented by

Arif Wibisono

ORCID: 0000-0003-1675-7617

for the degree of

Doctor of Philosophy

University College Cork

Business Information Systems

Head of School/Department: Prof Frédéric Adam

Supervisor(s): Prof David Sammon & Prof Ciara Heavin

2023

Table of Contents

Chapter 1 Research Overview 16

1.0 Introduction 16

1.1 Research Motivation 16

1.2 Research Background 17

1.2.1 Workaround Definition 18

1.2.2 Workaround Context: Report Production 20

1.2.3 Research Problematisation 22

1.2.4 Challenges in Data Governance 24

1.2.5 Data Governance Views: Authority vs Process 26

1.3 Research Objective, Questions, and Contribution 28

1.4 Research Philosophy 29

1.5 Research Design 31

1.5.1 Eisenhardt Method (EM) 32

1.5.2 Research Questions for Empirical Investigation 37

1.5.3 A Priori Constructs 38

1.5.4 Case Selection: Purposive Sampling 40

1.5.5 Collecting Data 43

1.5.6 Ethical Considerations 45

1.6 Research Roadmap 46

1.6.1 Phase 1: Literature Review 46

1.6.2 Phase 2: Methodology 46

1.6.3 Phase 3: Empirical Investigation 46

1.7 Research Output 49

1.8 Conclusion 50

Chapter 2 Literature Review 52

2.0 Introduction 52

2.1 *Paper* 1: Theorising workaround-centric data issues: a literature analysis 58

2.1.1 Introduction 58

2.1.2 Methodology 60

2.1.3 Literature Analysis 63

2.1.4 Findings and Discussions 74

2.1.5 Conclusion 81

2.2 *Paper* 2: Theorising workaround-centric data activities in information systems research 85

2.2.1 Introduction 85

2.2.2 Methodology 87

2.2.3 Literature Analysis 95

2.2.4 Findings and Discussion 103

2.2.5 Conclusion 112

2.3 Conclusion 119

Chapter 3 Research Methodology 120

3.0 Introduction 120

3.1 *Paper* 3: Plausible pictures for data governance: a narrative network approach 125

3.1.1 Introduction 125

3.1.2 Theoretical Background 128

3.1.3 Proposed Research Approach 132

3.1.4 Applying the Approach in a Hypothetical Scenario 136

3.1.5 Discussion: Plausible Pictures for Data Governance 142

3.1.6 Conclusion 144

3.2 Conclusion 147

Chapter 4 Empirical Investigation 148

4.0 Introduction 148

4.1 *Paper* 4: Data availability issues: decisions as patterns of action .. 157

4.1.1 Introduction 157

4.1.2 Research Methodology 159

4.1.3 Data Analysis 163

4.1.4 Findings and Discussion 167

4.1.5 Conclusion 172

4.1.6 Appendix 175

4.2 *Paper* 5: Values-driven workarounds to address data accuracy issues: Theorising from Indonesian field studies 177

4.2.1 Introduction 177

4.2.2 Theoretical Background 179

4.2.3 Research Methodology 183

4.2.4 Findings and Discussion 193

4.2.5 Kekeluargaan in Fast Authorisation Pattern 200

4.2.6 Conclusion 202

4.2.7 Appendix 208

4.3 *Paper* 6: Theorising approaches to identify data issues. 212

4.3.1 Introduction 212

4.3.2 Data Brokers as an Organisation 213

4.3.3 Research Approach: Data Gathering and Analysis 215

4.3.4 Findings and Discussion 217

4.3.5 Conclusion 226

4.4 Conclusion 229

Chapter 5 Conclusion 231

5.0 Introduction 231

5.1 Revisiting the Research Objective and Questions 232

5.1.1 Workaround-Centric Data Issues (RQ1) 232

5.1.2 Workaround-Centric Data Activities (RQ2) 234

5.1.3 Modelling WCDA (RQ3) 237

5.1.4 Patterns for 'Data Availability' Issues (RQ4) 238

5.1.5 Patterns for 'Data Accuracy' Issues (RQ5) 243

5.1.6 Patterns for Identifying Data Issues (RQ6) 248

5.2 Theoretical Contributions 251

5.2.1 Patterns of Action Summary 251

5.2.2 Contribution to Information Systems Research 253

5.3 Managerial Implications 256

5.3.1 Reflection: Democratising Data Governance 256

5.3.2 Recommendations For Data-Driven Organisations 258

5.3.3 Recommendations When to Use Patterns of Action 261

5.4 Research Limitations 263

5.5 Future Vision: Tribalistic Data Governance as an Alternate Model for Governing Data in Organisations 264

5.6 Further Research 270

5.7 Conclusion 271

References.....272

List of Tables

Chapter 1

Table 1.1 Workaround definition 19
Table 1.2 Phases and Research Questions 28
Table 1.3 Step-by-step in building theory (Eisenhardt, 1989) 33
Table 1.4 Research questions and their unit of analysis 38
Table 1.5 Shared Characteristics of Field Studies 41
Table 1.6 Field study in the research 42
Table 1.7 The Theoretical Sampling Strategy 43
Table 1.8 Potential problems that can emerge during data collection. 44
Table 1.9 Three phases, research questions, inputs, and outputs 48
Table 1.10 PhD project outputs. 49

Chapter 2

Table 2.1 Theorising WCDI and WCDA - Planning Worksheet (Baird, 2021, p. 1207) 54
Table 2.2 Workaround Examples 59
Table 2.3 Coding examples of data issues 66
Table 2.4 Workaround-Centric Data Issues and their frequencies 68
Table 2.5 Taxonomy of Workaround-Centric Data Issues (WCDI) 72
Table 2.6. Coding examples of types of workarounds and their data activities 93
Table 2.7 Types of workarounds and their frequencies 96
Table 2.8 Operational Definition of Workaround-Centric Data Activities 98
Table 2.9 Taxonomy of WCDA 102
Table 2.10 Distribution of Transferring Data in the Literature 105
Table 2.11 Coding example of Transferring Data 106
Table 2.12 Desired Behaviours for WCDA. 115

Chapter 3

Table 3.1 Extending Narrative Network - Planning Worksheet (Baird, 2021, p. 1207) 122

Table 3.2 The typology of action 130
Table 3.3 Rules to construct a narrative network. 132
Table 3.4 A hypothetical scenario (inspired by reality)..... 137
Table 3.5 Narrative fragments extracted from the scenario..... 139

Chapter 4

Table 4.1 Addressing Data Issues - Planning Worksheet (Baird, 2021, p. 1207) 150
Table 4.2 Interview Respondents..... 160
Table 4.3 Four steps in constructing a NN 161
Table 4.4 The Text Exemplars for Final Management Reporting 164
Table 4.5 The Text Exemplars for Collecting Daily Production Data..... 175
Table 4.6 Respondent Information..... 185
Table 4.7 Step-by-step to establish a NN..... 188
Table 4.8 Text Excerpts for Plantation Company..... 191
Table 4.9 Data Accuracy Issues and Solutions 205
Table 4.10 Text Excerpts for Government Agency 208
Table 4.11 Field Studies 215
Table 4.12 Text Generalisation..... 216
Table 4.13 Empirical investigation summary 230

Chapter 5

Table 5.1 Taxonomy of Workaround-Centric Data Issues (WCDI)..... 233
Table 5.2 Taxonomy of Workaround-Centric Data Activities (WCDA)..... 235
Table 5.3 Rules to model WCDA 237
Table 5.4 Step-by-step to construct a narrative network 237
Table 5.5 Summary of WCDA Patterns of Action 252
Table 5.6 Positioning this work against workaround literature 254
Table 5.7 Positioning this work against data governance literature 254
Table 5.8 Theoretical insights and contributions..... 255
Table 5.9 Recommendations for data-driven organisations 260
Table 5.10 Patterns of action by scenario 262
Table 5.11 Organisational functions of the data brokerage 265

List of Figures

Chapter 1

Figure 1.1 The onion diagram of workarounds as organisational processes ..20
Figure 1.2 Organisational Process and Workarounds.....38
Figure 1.3 The diagram of a data broker and its data providers. 42
Figure 1.4 Three phases in the research roadmap.....47

Chapter 2

Figure 2.1 Research Roadmap: Literature Review. 53
Figure 2.2 Search strategy.....64
Figure 2.3 Workaround domains where data issues manifest from the IS literature 65
Figure 2.4 Search strategy.....90
Figure 2.5 Workaround domains where data activities manifest from the IS literature. 91

Chapter 3

Figure 3.1 Research Roadmap: Research Methodology.....121
Figure 3.2 The scenario NN.....141

Chapter 4

Figure 4.1 Research Roadmap: Empirical Investigation 149
Figure 4.2 Narrative Network for Final Management Reporting. 169
Figure 4.3 Narrative Network for Collecting Daily Production Data.....171
Figure 4.4 Narrative Network of the Plantation Company 195
Figure 4.5 Narrative Network of the Government Agency. 196
Figure 4.6 Narrative Network of the University.....198
Figure 4.7 A data broker in an organisation 214
Figure 4.8 The data issues identification flow 225

Chapter 5

Figure 5.1 Dual Inspection and Prudent Control Patterns 240
Figure 5.2 Mindful Handling Pattern 241
Figure 5.3 Field Inspection Pattern 244
Figure 5.4 Fast Authorisation Pattern 245
Figure 5.5 Gold Standard Making Pattern 246
Figure 5.6 Flow to identify data issues 249
Figure 5.7 A unified pattern to fix data issues. 252
Figure 5.8 Emerging coordination structure: data brokerage. 265
Figure 5.9 Tribalistic Data Governance – this study posits that effective data governance must start in a data tribe. 267
Figure 5.10. Complementing Traditional and Tribalistic Data Governance. 268

Declaration

"This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism and intellectual property."

Digital signature of the candidate: ---------- Arif Wibisono.

Acknowledgement

Alhamdulillah. All praise is due to God, Lord of all worlds, who allows me to finish this remarkable PhD Journey. The journey was intellectually, spiritually, and emotionally draining. Many *surprising* things happened, and they were beyond my control. On the one hand, the journey was like being *trapped in a nightmare* and never waking up. On the other hand, it pushed me to new limits I did not expect before. It helps me reflect on myself and be grateful for everything I have.

Despite all hardships during this journey, I am glad to have been surrounded by many lovely individuals. While it is impossible to mention everybody, I would like to try to honour those who played a significant part in my PhD journey.

First, I want to express my heartfelt gratitude to my PhD sponsors. First, the Higher Education Authority (HEA) has provided me with the prestigious *Government of Ireland – International Education Scholarship* (GOI-IEA) for Year 1. Second, the Department of Business Information Systems (BIS), University College Cork (UCC), Ireland, with its *PhD bursary* program for Year 2 to Year 4. Third, the Indonesia Endowment Funds for Education (LPDP), Ministry of Finance Indonesia, *indirectly* supported my study by providing a scholarship and allowance to my wife.

Also, I would like to thank my supervisors, Prof. David Sammon and Prof. Ciara Heavin, for their time, efforts, the breadth of their research expertise, experience, tireless support, contagious enthusiasm, and ever-insightful feedback.

Next, I would like to thank Prof. Joseph Feller, the then Head of Department, for his support and assistance along the journey. Prof Frédéric Adam, for all his kindness as my internal examiner, the current head of the department, and an *insightful* teacher since the very humble beginning of this PhD topic. Prof Jan vom Brocke (University of Liechtenstein) as my external examiner. Given my two examiners. I was fortunate to be examined by two

distinguished professors in Decision Making and Business Process Management on December 8th, 2022. It was a great *online* discussion session lasting around 3 hours and 20 minutes.

My sincere gratitude goes to my wonderful *late* wife, Amna Shifia Nisafani, who was present for every moment before and on the journey. She was the one that recommended BIS UCC for our PhDs together and was the best friend to discuss everything. Her *sudden* passing in our flat in Cork (2021) somewhat *changed* the course of this journey and my life.

Therefore, I would like to thank all Muslim communities and UCC communities that helped me during our stay in Ireland and helped with Amna's burial in Cork, Ireland. Particularly Abang Wan, Kak Ina, Bu Yuli, Mas Lintang, Ariq, Karim, Uni Yenni, Bang Febri Marsa, Mbak Kadek, Dr Marcel Jinih, Zainab Alshabeeb, Oluchi, Dr Ibrahim Alhassan, Ms Marita Foster, Ms Anne-Mary Scary, Ms Cliona Maher, Dr Gaye Kiely, Dr Carolanne Mahony, Dr Karen Neville, Dr Long Pham, and Dr Simon Woodworth.

Additionally, I'd like to convey my gratitude to my Indonesian communities that gave support when Amna passed away. Particularly Bu Hanim, Bu Irma, Bu Anisah, Pak Rully Hendrawan, Bu Vivin, Bu Renny, Pak Nisfu, Pak Andre, Bu Erma, Bu Mahendrawathi, Bu Amalia, Bu Ika, and Reza Sufara. This gratitude goes to Indonesian Ambassador to Great Britain and Ireland, Dr Desra Percaya, in the UK, then Institut Teknologi Sepuluh Nopember (ITS) Rector, Prof Joni Herman, ITS Rector Prof Muhammad Ashari, Dean Dr Ketut Eddy, Vice Dean Dr Diana Purwitasari. Their supports were priceless for me when I faced my lowest points abroad.

Ultimately, I am immensely thankful to my family (my father, Sutardi, my mother, Pestariati, my siblings: Dek David & Dek Tiwi, my father-in-law Yanani, and my sisters-in-law – Mbak Ninda, Mbak Nia, and Dek Vida) for their constant encouragement and support. Their loves and supports are genuine and dependable. Thank you very much.

Dedication

To remember:

Amna Shifia Nisafani

(1987-2021)

My wife, a friend, a *loving* mother,

A PhD fellow in Business Information Systems,

University College Cork

She *suddenly* passed away in our flat (during our PhD studies *abroad*),

on the 22nd of February 2021: at 16:14 GMT.

Buried in the Muslim Section,

At Saint James Cemetery, Chetwynd, Country Cork, Ireland.

She brought us to Ireland and (sadly) caused us to leave.

However, she is always the reason we must return someday.

Abstract

Data issues are detrimental and costly for organisations. So, this study investigates how employees pragmatically execute patterns of action to fix data issues. Each pattern is built upon linked workaround-centric data activities (WCDA), which are overlooked in current data governance and workaround research. Five field studies in Indonesian organisations are conducted to achieve this objective. They include a plantation company, a furniture manufacturer, a hospital, a government agency, and a university.

As the research roadmap, this study conceptualises workaround-centric data issues (WCDI) and activities (WCDA) from workaround literature as taxonomies. Next, it extends a narrative network approach to model WCDA. In the end, it investigates five organisations to capture two things. First, it captures *WCDA patterns of action* to fix data issues. Second, it captures how employees *identify data issues* before fixing them.

This research reveals several findings. First, workaround literature suggests that data *availability* and *accuracy* are the most frequently occurring issues. Second, the empirical work suggests that data availability and accuracy issues introduce six action patterns. It reveals that *evaluate data* (part of WCDA) is the common denominator for these patterns. Third, as part of *evaluating data*, employees execute five "checking" approaches to identify data issues: check *data templates,* check *supervisor validation,* check *data accuracy,* check *data consistency,* and check *data completeness*.

There are three significant contributions to data governance and workaround research. First, this study challenges the mainstream assumption in data governance research. It suggests that addressing data issues must be *preventive* practices (e.g., pre-determined, top-down, and *before* the data are produced). This research shows that *curative* practices (e.g., reactive, bottom-up, and *after* the data are produced) are the norm. They exist to address immediate data needs such as managerial reporting.

Second, this research challenges two widely held assumptions in workaround research: 1) a workaround is an atomic process, and 2) a workaround is an isolated process. It opens the workaround black box and shows that a workaround can consist of interlinked WCDA (e.g., a pattern of action). So, a workaround is neither atomic nor isolated.

Third, this study progresses our understanding of WCDA and their relationships (as patterns of action). It identifies WCDA types from the literature. After that, it identifies WCDA patterns to address data issues from field studies. These patterns provide non-managerial employees with plausible pictures to govern data with minimal top-management intervention.

These patterns allow employees to reflect on their work and present these creative practices to top management whenever necessary. Therefore, these patterns democratise data governance in organisations by making governance meaningful for operational employees. In the end, this research discusses theoretical contributions and managerial implications for data governance research and practices.

Chapter 1
Research Overview

1.0 Introduction

The purpose of this chapter is to provide an overview of this study. It explains the research motivation, background, philosophy, design, roadmap, and output. First, Section 1.1 highlights the real-world problem of data issues, which motivates this research. It explains how these issues can be catastrophic for organisations. Second, Section 1.2 problematises the current workaround and data governance literature. By doing so, it introduces relevant research questions. Third, Section 1.3 explains the research objective, questions, and contributions. Fourth, Section 1.4 outlines and describes the research philosophy. It underpins this study's ontological and epistemological position. By doing so, one can describe the nature of the theories produced from this research. Fifth, Section 1.5 explains the research design. In doing so, the research methodology explains the field study selection and the approach to data collection. Sixth, Section 1.6 explains the research roadmap. As such, it shows three phases of this research. Next, Section 1.7 highlights the research outputs. To do so, it shows the status of the publications associated with this research project. Lastly, Section 1.8 concludes this chapter.

1.1 Research Motivation

Data issues are challenging and expensive for organisations. They can result in a high cost for many companies (Altendeitering & Tomczyk, 2022; Fürstenau et al., 2021; Goff et al., 2021; Manga & Xiao, 2020). Previous studies show that data issues can raise operational costs, decrease job satisfaction, and increase internal organisation mistrust (Altendeitering & Guggenberger, 2021; Daneshkohan et al., 2022; Haug et al., 2011; Redman, 1998).

This amount could be 8–12% of revenue or 40–60% of a service organisational expense (Redman, 1998). Also, data issues are responsible for

$15 million a year in losses for an average company (Altendeitering & Guggenberger, 2021).

Data issues inflict difficulties in positioning and executing business strategies (Redman, 1998). They profoundly affect every level of an organisation (Nagle et al., 2020). They can impose wide-ranging economic and social consequences as time passes if the organisation fails to identify and rectify them (Haug et al., 2011). So, a research project that *theorises* how employees deal with these data issues can help bring awareness to organisations. The following section discusses the research background that facilitates this research project.

1.2 Research Background

As to the research background, this section discusses four things.

First, Section 1.2.1 describes the research definition. It shows what constitutes a workaround and what does not. It compares workarounds and standardised processes in organisations.

Second, Section 1.2.2 explains the context for our research. This research mainly focuses on the workarounds used in producing managerial reports in a centralised system environment. The study investigates the advantages and disadvantages of various reporting cycles in the report production process. It highlights the significance of comprehending the patterns of action in report production when data availability and accuracy issues arise.

Third, Section 1.2.3 explains how this study *problematises* (Alvesson & Sandberg, 2011; Sandberg & Alvesson, 2011). This problematisation facilitates researchers to develop research questions by *challenging assumptions* employed in the current research (Sandberg & Alvesson, 2011). So, it enables researchers to establish alternative perspectives on the phenomenon (Chatterjee & Davison, 2021) and produce significant and interesting theories (Sandberg & Alvesson, 2011).

Fourth, Section 1.2.4 discusses the theoretical inadequacies in data governance literature. It shows that various workaround examples from

workaround literature can compensate for these inadequacies. So, both bodies of literature are relevant and complement each other. They facilitate the emergence of theories explaining how an organisation addresses data issues.

Fifth, Section 1.2.5 explains current views of data governance. It shows two types of data governance views: authority-centric and process-centric. It explains how this study views data governance as a process to capture *curative* practices to address data issues.

1.2.1 Workaround Definition

This section provides an operational definition of workarounds. This definition helps to define the central concept (e.g., workarounds) by *stating how it would be observed* (Denzin, 1978). As such, this study defines workarounds as "*adaptive processes occurring in a centralised system environment*" (Wibisono, Sammon, & Heavin, 2022b, p. 1). They are purposeful in achieving a specific objective in an organisation given particular difficulties (Alter, 2014; Morrison, 2015; Röder et al., 2015).

Workarounds are not *random* processes (Dunford et al., 2017). A physician, for example, because of a *data access issue*, violates medical confidentiality regulations by providing a patient's data from an Electronic Health Record to other colleagues (see this action as a workaround). Thus, by executing this workaround, the physician can solicit colleague feedback (Röder et al., 2015; Röder, Wiesche, & Schermann, 2014). Unlike standardised processes, this workaround exceeds top management's guidelines, rules, and regulations.

In addition, centralised systems encompass digital artefacts that store any organisational data centrally (see Table 1.1). These artefacts are in a continuum. They can be as complex as Enterprise Resource Planning (ERP) or Electronic Health records (EHR). However, they can also be as simple as a file hosting service to store data (e.g., Dropbox, Google Drive).

Moreover, data issues trigger a workaround to materialise (Azad & King, 2012). For example, the issues with data *availability* (Bozan & Berger,

2018; Van de Weerd et al., 2019), data *accuracy* (Huuskonen & Vakkari, 2013; van den Hooff & Hafkamp, 2017), data *consistency* (Drum et al., 2017; van den Hooff & Hafkamp, 2017) and data *completeness* (Safadi & Faraj, 2010; Ser et al., 2014) hinder employees from achieving their work tasks on time. So, employees create workarounds as *curative* practices to fix these data issues. These workarounds can help the employee to produce urgent mandatory reports for various stakeholders (Wibisono, Sammon, & Heavin, 2022a).

Table 1.1 Workaround definition

No	Aspect	Workaround	Standardised Process
1	Adaptive processes	✓	
2	Centralised systems	✓	✓
3	Addressing data issues	✓	
4	Use data artefact	✓	✓
5	Has an objective	✓	✓
6	Organisational context	✓	✓

As such, these workarounds must incorporate data artefacts to manifest. These artefacts can be either hardware, software, physical papers, or cloud services. For this research, using data artefacts is a must. *Curative* practices over the above issues only apply if data artefacts are used. Otherwise, these *curative* practices cannot manifest.

Likewise, workarounds must have organisational backgrounds (Alter, 2014; Behrens, 2009; Györy et al., 2012; Silic & Back, 2014). In this case, any personal situation is not applicable. Consider an individual who works around a gamification-driven mobile health app. The app calculates the number of footsteps an individual takes in a day. The app then gives this individual a point based on produced footsteps at the end of the day. One may work around this app by riding a bike slowly to mimic walking activities. This action can be a workaround (because it deviates from the use intention of the app's original

designer). However, this research does not consider it a workaround because of the absence of organisational contexts.

1.2.2 Workaround Context: Report Production

This research characterises a workaround as a subset of an organisational process (see Figure 1.1). A workaround can serve multiple *generic* purposes, such as increasing the efficiency or effectiveness of current organisational processes (Wolf et al., 2020) or completing work tasks (Fürstenau et al., 2021). It contains workaround-centric data activities (WCDA), and each data activity consumes, transfers, and produces data (see Figure 1.1).

This research emphasises workarounds and data activities for *managerial* report production. This type of process is ever present in organisations. Every organisation must produce reports for planning, controlling and evaluating its operations (Drum et al., 2017). Otherwise, the organisation would experience runaway costs and uncontrolled risks.

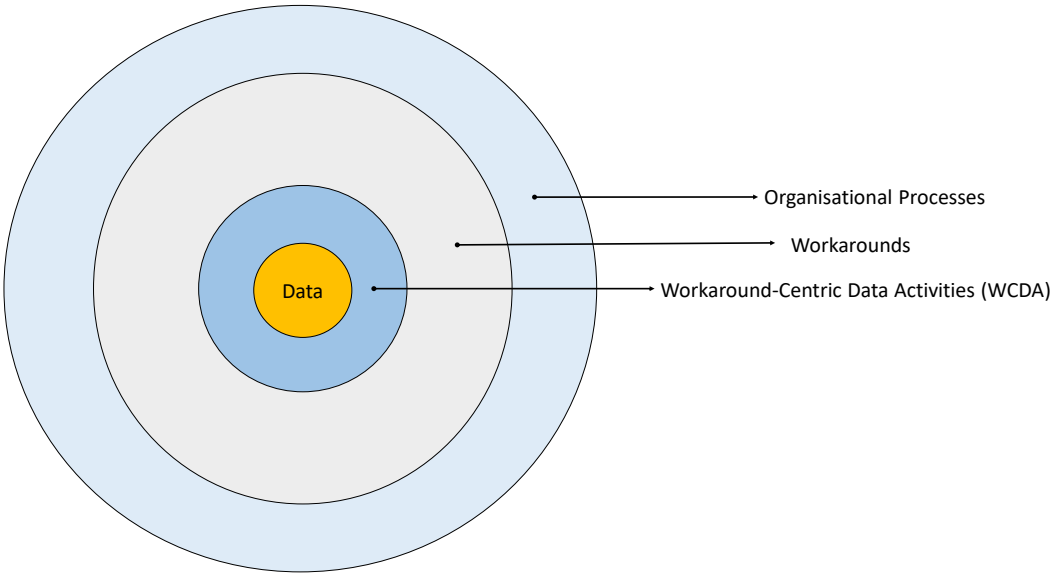

Figure 1.1 The onion diagram of workarounds as organisational processes

Furthermore, this research also views workarounds as necessary, given the inadequacies of a centralised system (e.g., ERP, EHR) in addressing reporting needs. Therefore, employees execute workarounds to produce a

managerial report for the organisation outside the centralised system. Hence, the required report (based on good quality data) can be available on time (within its reporting cycle). Given these reasons, this research examines organisations based on their reporting cycles.

Previous research shows that organisations can have various reporting cycles (Horngren et al., 2018). On the one hand, shorter reporting cycles, such as weekly or daily reporting, can provide more up-to-date data. They enable managers to make more informed decisions faster (Kaplan & Norton, 1996). However, they can also burden employees responsible for producing the reports. This situation can result in more frequent interruptions to work (Pirttimäki & Liew, 2019). Shorter reporting cycles may also result in less detailed or less comprehensive reports. One reason is that there may not be sufficient time to gather and analyse all the relevant data (Hansen & Schaltegger, 2016).

On the other hand, longer reporting cycles can provide a more comprehensive and detailed view of an organisation's performance. They allow more data to be collected and analysed (Weygandt et al., 2014). However, they may also result in delays in decision-making, as the data are unavailable until the end of the reporting period. This situation can be a disadvantage in a fast-paced organisation where timely decisions are crucial.

Despite their differences in reporting cycles, these organisations must share similar activities to generate reports. For example, a systematic approach to data collection is necessary to ensure that the information provided in the report is accurate and reliable (Bhimani & Bromwich, 2009; Hansen & Mowen, 2018; Horngren et al., 2018). This approach can involve setting up systems to track data, collecting data from various sources, and verifying the accuracy of the data (Bhimani & Bromwich, 2009). This research examines how organisations execute these activities as *patterns of action*, mainly when specific data issues (e.g., availability, accuracy) materialise in a centralised system.

Overall, both definition and context see a workaround as a socio-material process that puts humans, technology, and data at its centre (Alter, 2014). This definition facilitates *further* research problematisation.

1.2.3 Research Problematisation

This study challenges two widely held beliefs in workaround research by following *research problematisation* (Alvesson & Sandberg, 2011; Sandberg & Alvesson, 2011).

First, workaround research assumes a workaround is a composite, atomic, and non-divisible process. Second, research presumes that a workaround is a standalone procedure. For example, workarounds in Barcode Medications were researched by Koppel et al.(2008). They demonstrate specific "atomic" workarounds, such as "User scans medicine from the patient drawer without visual inspection" or "User dispenses medication without scanning patient ID." These examples provide a workaround in the form of an atomic and isolated object.

Vogelsmeier et al. (2008) enhanced these examples by demonstrating that a workaround consists of two interconnected processes. Each action, however, is inadequately atomic. "Prepare to send printed orders to a pharmacy," for example. In this case, "prepare" may be split into more atomic steps, such as *retrieving* items from a shelf and *storing* them in a folder.

These two assumptions also turn out to be false. For example, why do two seemingly similar workarounds result in disparate outcomes from a data perspective? Consider two workarounds with the same name: "*a doctor analyses patient data from the centralised system from home*" (Röder, Wiesche, & Schermann, 2014), which can have different impacts. The first workaround involves the doctor *downloading* the data and *emailing* it to other doctors via a business email. They may therefore evaluate the outcome at home (Röder et al., 2015). The second workaround is for the doctor to *download* the information, *put* it on a USB drive, and *take* it with them (Silvius & Dols, 2012). Because a

USB stick may disappear (via theft or accidental dropping, for example), the organisation *can* violate its data security and protection measures.

The WCDA concept (Wibisono et al., 2020; Wibisono, Sammon, & Heavin, 2022c) challenges these presumptions. Instead of relying on these presumptions, this research uncovers the workaround by joining two or more atomic actions (such as WCDA). Hence, researchers can better comprehend the complexities of tackling organisational data issues.

This study also **challenges** a widely held belief in previous data governance research: solving data issues requires a *preventive* practice (Batini et al., 2009; Nagle et al., 2020; Pipino et al., 2002; Sebastian-Coleman, 2013). It demonstrates that this practice can also be *curative* as well.

Preventive practices are pre-determined, top-down, and *before* the data are produced. For instance, Batini et al. (2009) propose a data-driven strategy and process-driven methods for avoiding data issues. The data-driven strategy includes acquiring new data, record linkage, and data and schema integration. The process-driven method encompasses process control and process redesign. Here, three sets of actions are suggested by Pipino et al. (2002) to prevent data issues: 1) conducting subjective and objective evaluations of the data quality; 2) comparing the outcomes of the assessments, discovering inconsistencies and identifying the reasons for disparities; and 3) deciding on and implementing the necessary measures for improvement.

These practices are superior for creating universal and comprehensive solutions to tackle data issues. However, *preventive* practices require careful monitoring, a long deployment, and post-deployment supervision. Unfortunately, infrastructure issues (Born & Krönung, 2016), lack of skilled people (Steinhueser et al., 2017), poor software functionality (Davison et al., 2019; Ibrahim et al., 2019), and poor software usability (Jagannath et al., 2019; van den Hooff & Hafkamp, 2017) can present challenges for an organisation. These challenges can hamper the organisation from providing quality data when needed. Further, the pressing data needs of various stakeholders (e.g.,

reporting) force its operational employees to correct data issues once found (Wibisono, Sammon, & Heavin, 2022a).

As a result, employees enact a *curative* practice to creatively manage data beyond the centralised system (cf. Wibisono, Sammon, & Heavin, 2022a). *Curative* practices themselves are reactive, bottom-up, and *after* the data are produced. Employees can collect, analyse, transform, and transfer the data to appropriate parties. By doing so, the current data are suitable for future use (e.g., reporting). Indeed, research shows that the reality of addressing day-to-day data issues is (actually) more *curative* than *preventive* (cf. Wibisono, Sammon, & Heavin, 2022a). Even though these *curative* practices are essential to producing quality data, they are overlooked in current research.

1.2.4 Challenges in Data Governance

Understanding *curative* practices are essential. However, it is underrepresented in data governance research. As such, data governance literature remains silent on how *curative* practices manifest because it perceives these practices as inefficient and wasteful.

There is a metaphor in data governance for *curative* practices: *hidden data factories* (Redman, 2016b). Operational employees typically work around or rectify many data issues. However, the expenditures are significant. Research shows that knowledge workers squander up to 50 per cent of their time managing data issues. For example, discovering & fixing mistakes and seeking to validate sources for data they do not believe in (Redman, 2013). So, instead of managing these *curative* practices, organisations had better remove them (Nagle et al., 2020).

Unfortunately, the understanding of totally removing *curative* practices can be misleading.

First, *completely* eradicating data issues from an organisation is almost impossible. As organisations work harder to be data-driven, the number of data participants increases. As a result, the potential to produce data issues is (also) increasing (e.g., errors in inputting data). Once a data issue occurs, a *curative*

practice must be undertaken. Otherwise, the organisation cannot meet its immediate quality data needs.

Second, data reflects a phenomenon of interest. However, the reflected phenomenon can change over time *unexpectedly*. For example, some products can be damaged or lost in the warehouse. As a result, the previously entered data can be obsolete and inaccurate. So, another employee must execute a *curative* practice to fix the data in this situation.

. While data governance literature lacks *curative* practice theorisation, the workaround literature has many examples of data-related creative practices (e.g., workarounds). These practices have great potential to theorise *curative* practices. For example, consider a patient's data becoming unavailable because the central system crashes. So, the physician *writes down* patient data on a paper-based file (Blijleven et al., 2019).

Similarly, because SAP has limited analysis capabilities, employees *extract* SAP data and *consolidate* them with a spreadsheet for further analysis (Li et al., 2017; Wolf & Beverungen, 2019). *Writing down, extracting,* and *consolidating data* are activities manifested within a workaround. Therefore, this study refers to these activities as workaround-centric data activities (WCDA).

Workaround research discusses WCDA a lot. However, they are not the real focus of the investigation. Instead, researchers tend to describe WCDA as part of more general topics such as *compliance and data protection* (Burns et al., 2015; Eikey et al., 2015; Silic et al., 2017; Sillic, 2019; Walters, 2013), *adoption and resistance* (Alraddadi et al., 2018b; Behrens, 2009; Bozan & Berger, 2018; Malaurent & Avison, 2016; Zamani et al., 2013)*, organisation misalignment* (Beerepoot & van de Weerd, 2018), *coordination* (Djalali et al., 2015), and *information quality* (Bozan & Berger, 2018; Drum et al., 2017). Therefore, the understanding of data issues, their WCDA, and produced *curative* practices remains incomplete.

1.2.5 Data Governance Views: Authority vs Process

Understanding *curative* practices relates to how one views data governance itself. Data governance is a broad term that falls into two streams in current research (Zhang et al., 2022).

The first stream emphasises an *authority* view: the control and exercise of decision-making over data to turn data into strategic enterprise assets (Khatri & Brown, 2010). It specifies decision-making rights to treat data (Nielsen, 2017). It develops standards, policies, and procedures to treat data (The Data Warehousing Institute, 2010). Also, it emphasises top-down hierarchical structures. Each structure provides rules and controls data assets (Ladley, 2020). These structures also set data-related goals. They specify high levels sets of tasks (Plotkin, 2014). So, organisations can establish a holistic approach to managing data. Thus, a data governance program can deliver the *usefulness of data* and its *value characteristics* as an asset.

The second stream emphasises a *process* view (Zhang et al., 2022). This view sees data governance as a data processing approach to address organisational data issues such as availability, quality, privacy, consistency, usability, quantity, and security (Berson & Dubov, 2011; Cheong & Chang, 2007). It highlights "process", not "things". It focuses on *action* and *relations between actions* (e.g., patterns of action) (Pentland & Feldman, 2007) to address data issues. In short, this view is an *action-centric perspective* (Feldman, 2016). It captures an organisation as a set of processes central to governing and managing data. It differs from most data governance models, which are more authority-centric.

This research uses the second view of data governance: **governance as a process.** This view is appropriate for understanding *curative* practices that are mostly "grounded" on the bottom of the organisational pyramid. As they are "grounded", they may not have *clear* and *pre-determined* holistic standards, policies, procedures, and roles – compared to authority-centric data governances. So, an authority-centric view cannot capture *curative* practices well. There are more reasons to explain this situation.

First, data requirements are prone to changing rapidly over time (M. Becker, 2007). Hence, efficiently revising rules and policies can be challenging to accommodate, especially when the rules and policies are complex and intertwined. Operational employees may not use current rules and policies when fixing data issues and addressing pressing data needs.

Second, poor IT infrastructure (Born & Krönung, 2016; Stevenson et al., 2018), poor software usability (Baysari et al., 2018; van den Hooff & Hafkamp, 2017), software dysfunctionalities (Ibrahim et al., 2019; Van de Weerd et al., 2019), and employee coordination problems (Niazkhani et al., 2011; Walterbusch et al., 2017) are prevalent events in organisations. They *can* hinder data governance authorities. So, operational employees work around these events (e.g., *curative* practices) to govern data.

Third, the imposed regulations, rules, procedures, and standards differ from employees' mental models (Saleem et al., 2009). So, employees may think these regulations, rules, procedures, and standards are sub-optimal or (even) useless for addressing day-to-day variabilities (Huuskonen & Vakkari, 2013). These standardisations are obstacles instead of solutions. Hence, instead of following these standardisations, employees use their mental models to respond to their situational needs (Saleem et al., 2011). Therefore, given these facts, understanding *curative* practices through an authority-centric view can be misleading.

Furthermore, to operationalise the research design, this study defines data governance as "**the *process* of managing data issues such as data availability, accuracy, consistency, completeness, accessibility, and security**". So, it produces descriptive understandings, narrative accounts, and explanations (Mendling et al., 2021) in *managing data issues.*

As this research views data governance as a "process", it blacks boxes many components of traditional data governance. These components include data strategy, policies, procedures, and organisational structures (Abraham et al., 2019; Al-Ruithe et al., 2018; Koltay, 2016; Romero et al., 2019). It only focuses on how the *process* of managing data materialises. By doing so, the

produced theoretical insights (e.g., patterns of action) can be more relevant, parsimonious, and generalisable (Pentland & Feldman, 2005).

1.3 Research Objective, Questions, and Contribution

Research suggests that the output of *research problematisation* is the research objective and questions (Alvesson & Sandberg, 2011; Sandberg & Alvesson, 2011). So, following the research problematisation in Section 1.2.3, this study poses the following research objective:

Research Objective:
To explore WCDA *patterns of action* as *curative practices* to address *data issues.*

This research divides the timeline into three phases: literature review, methodology, and empirical investigation to address the research objective. Each phase has its research question(s). Overall, this study introduces six research questions (see Table 1.2).

Table 1.2 Phases and Research Questions

Literature review
RQ1. What are Workaround-Centric Data Issues (WCDI) in organisations? RQ2. What are Workaround-Centric Data Activities (WCDA) in organisations?
Methodology
RQ3. How are modelling rules used to model WCDA?
Empirical Investigation
RQ4. What are the WCDA patterns of action triggered by data availability issues? RQ5. What are the WCDA patterns of action triggered by data accuracy issues? RQ6. How do employees identify data issues in WCDA?

There are three theoretical contributions to data governance and workaround research.

First, this study challenges the widely-accepted assumption in data governance research: organisations must apply *preventive* practices (e.g., pre-

determined and top-down) to navigate data issues. Instead, this research shows that *curative* practices (e.g., reactive and bottom-up) are everyday practices for navigating data issues.

Second, this study challenges two prevalent assumptions in workaround research: 1) a workaround is an atomic process, and 2) a workaround is a solitary process. It exposes the workaround black box and illustrates that a workaround contains interlinked WCDA (e.g., a pattern of action). So, a workaround is neither atomic nor solitary.

Third, this research progresses the understanding of WCDA and its connections (as patterns of action). It identifies WCDA types from the literature. Also, it identifies WCDA types and their patterns of action from empirical work to fix data issues. By doing so, workaround research communities can better comprehend the nature of these patterns of action.

1.4 Research Philosophy

This study undertakes *interpretive research* to address the research questions posed. The use of this strategy for workaround research is widespread. For example, Ignatiadis & Nandhakumar (2009) undertake an interpretive research strategy to understand the influence of ERP workarounds on organisational controls. Malaurent & Avison (2011) examine the emergence of informal organisation structures to address local needs in an ERP deployment. Khalil *et al.* (2017) differentiate the knowledge and expectations between IT and business stakeholders on cloud IT.

First, regarding the ontological position, workarounds are the organisational locus of the investigation. So, this research designates workarounds as the "world". It takes *constructivism* as the ontological position. This position argues that workarounds are social phenomena where social actors continually realise their meanings. They are not static objects and are constantly changing over time. Research shows that for serving the same goal, a workaround can have multiple versions in reality (Haag et al., 2015). So, the

research outputs *can* only theorise a particular version of workarounds (not all workaround versions).

This ontological position is appropriate, given that a workaround is an organisational process. It fits with previous research denoting that a process *varies* across individuals and events (Pentland & Feldman, 2005). It produces *multiple versions* (Feldman & Pentland, 2003; Pentland et al., 2020) and involves *multiple actors* in its execution (Feldman & Pentland, 2003; Pentland & Hærem, 2015). Hence, it produces *multiple understandings* and *interpretations* for each employee (Pentland & Feldman, 2005). In short, there is no single objective process but an array of distinctive viewpoints on what is happening (Feldman & Pentland, 2003).

Second, the empirical focus is to capture the *belief* of its actors in addressing data issues. This belief manifests as a set of narratives later articulated as a sequence of actions. This belief is analogous to the *ostensive* aspect of the theory of organisational routines (Feldman & Pentland, 2003). The *ostensive* aspect is a process's ideal or schematic form (Feldman & Pentland, 2003). It constitutes each actor's understanding (Pentland & Feldman, 2008). It is neither a written rule nor a procedure. However, it guides an organisation to materialise a process (Pentland & Feldman, 2005).

Focusing on the *ostensive* aspect provides *coherence* while analysing distributed processes that seem disconnected (Pentland & Feldman, 2007). It facilitates the contextual understanding of workaround manifestations across units. Also, it enables the comparison of the worldviews of multiple actors in executing workarounds (Pentland & Feldman, 2005). So, this study can establish a better *abstract idea* of the process (Feldman & Pentland, 2008), which is essential for theorisation.

Third, as part of the empirical examination, this research uses *etic* (outside observer) as the viewpoint (Walsham, 1995). As such, it does not engage process participants. By doing so, it can be *culturally* neutral across field studies. This stance is critical because it can analyse how a particular culture informs emerging patterns of action to fix data issues.

Fourth, the research output is understanding (*verstehen*). *Verstehen* is a subjective meaning that emphasises each actor's viewpoint (Goldkuhl, 2012). One can see it as an *empathic understanding* of human behaviours. This understanding must surface from dialectical movements between the holistic understanding and the understanding of singular parts (Goldkuhl, 2012). In this case, the understanding manifests as WCDA patterns of action to fix data issues.

Fifth, the role of knowledge in this research is *interesting.* This *interestingness* (Murray, 1971) emerges by selecting the "framing on workarounds". In this case, workarounds are framed as *creative* practices that help the organisation *address* data issues. So, they are *positive*. This framing contradicts the mainstream understanding that workarounds *negatively* impose data issues (Behrens, 2009; Ignatiadis & Nandhakumar, 2009; Stevenson et al., 2018; Wolf & Beverungen, 2019). Hence, they are the source of data *compliance problems* (Brooks et al., 2015; Drum et al., 2016; Fürstenau & Rothe, 2014) and *poor decision-making* (Bozan & Berger, 2018; Drum et al., 2017). Therefore, this positive framing is "potentially" interesting for workaround research communities.

Sixth, the type of investigation is field studies informed by Eisenhardt (1989). This investigation strategy inductively examines the phenomenon (e.g., workarounds) by continuously comparing data and reality. So, one can identify patterns and relationships (Ridder, 2017) to create novel theories in workarounds.

Seventh, for data generation, *open coding* (Corbin & Strauss, 1990) is used as a tool for interpretation. This study interviews some participants from five organisations. Interviews are recorded and transcribed into texts. Afterwards, these texts are analysed using open coding.

1.5 Research Design

This section explains how this research uses an exploratory field study, informed by Eisenhardt (1989), which is later called the "*Eisenhardt Method*"

(EM) (2021). The use of EM to inform interpretive research is justified by Walsham (1995). He indicates that some aspects of EM are relevant for interpretive research. For example, EM is related to the function of the theory in research: 1) as an initial guide to design and data collection, 2) as part of an iterative process of data collection and analysis, and 3) as a final product of the research (Walsham, 1995, p. 76).

However, while EM advises researchers to test their final theory, interpretive research does not suggest doing so (Walsham, 1995). Theories in interpretive research are the "*products of both material and social dimensions*" (Walsham, 1995, p. 76). So, any testing cannot fully capture the complexity of these dimensions. Therefore, testing is not mandatory in interpretive research.

The following section briefly explains what EM is and its rationale. Also, this research shows both advantages and disadvantages of employing EM. Further, it shows the step-by-step to undertaking the EM. This understanding is essential to guide empirical work. Therefore, the researcher can manage complexity during the field work. This understanding is also pivotal for ensuring the replicability of the study.

1.5.1 Eisenhardt Method (EM)

As the research questions of workarounds are phenomenon-driven, using EM is necessary (Eisenhardt & Graebner, 2007). These phenomenon-driven research questions address the lack of plausible existing theories (Eisenhardt & Graebner, 2007), especially in explaining data issues and their produced workarounds. Furthermore, some data activities in workarounds can produce data opportunities (if correctly undertaken), e.g., promoting data quality (Bozan & Berger, 2018).

However, this viewpoint seems underexplored because workaround research perceives workarounds *negatively* (Baysari et al., 2018; Huber et al., 2018). Hence, researchers need to fill the knowledge gap of data activities in workarounds and their data impacts by doing empirical work. In doing so, this study employs EM (Eisenhardt, 1989).

Table 1.3 Step-by-step in building theory (Eisenhardt, 1989)

No	Step	Action	Motivation
1	Getting Started	Define research questions.	To keep the study focused so that researchers can manage the data volume.
		Use a priori constructs.	To set up accurate measures for each construct.
		Use neither theory nor hypothesis.	To keep theoretical flexibility
2	Selecting Fields	Determine the relevant population.	To keep the study focused so that it can ensure that the data volume is manageable.
		Use theoretical sampling (not statistical random sampling).	To focus efforts (only) on fields that produce a theory.
3	Crafting Instruments and Protocols	Use multiple data collection methods.	To strengthen the grounding of the emergent theory – by providing a means of triangulation.
		Use both qualitative and quantitative data.	To synergise how this study views the evidence.

		Use multiple investigators.	To promote divergent viewpoints and to strengthen the grounding of the emergent theory.
4	Entering the field	Use field notes to overlap both data collection and data analysis.	To speed up the analysis and guide helpful adjustment to data collection.
		Use flexible and opportunistic data collection.	To enable researchers to benefit from emergent themes and specific case features.
5	Analysing Data	Use within-case analysis.	To obtain familiarity during field studies with data and to generate preliminary theory.
		Use divergent techniques to generate cross-case patterns.	They can see evidence from multiple viewpoints to push researchers to examine any findings beyond their early impressions.
6	Shaping hypothesis	Tabulate evidence for each construct (iteratively).	To establish three things: construct definition, validity, and measurability.

		Use replication logic – not sampling logic.	To confirm, sharpen, and extend the emergent theory.
		Examine the evidence for constructing relationships – by asking "why."	To set up internal validity.
7	Enfolding literature	Examine the emergent theory with conflicting findings from the literature.	To increase the emergent theory's confidence by achieving internal validity, raising the theoretical level, and sharpening construct definitions.
		Examine the emergent theory with similar findings from the literature.	To sharpen the emergent theory's generalisability, enhance the construct definition, and raise the theoretical level.
8	Reaching closure	Achieve theoretical saturation (when possible).	To know when to end the process. That is when improvements are marginal.

The EM is a methodology for theory-building (Eisenhardt, 1989; Eisenhardt & Graebner, 2007; Ridder, 2017). Therefore, the outputs can be theoretical constructs, prepositions, or mid-range theories from evidence obtained during the field studies (Eisenhardt, 1989; Eisenhardt & Graebner, 2007). The EM attempts to understand each case individually and comprehensively. So, it does not produce summary statistics (Eisenhardt, 1989).

The EM process is highly iterative and tightly linked to the data (Eisenhardt, 1989). The iterative process includes constant forward and backwards between steps (see Table 1.4). Further, the iterative process can involve one or more fields (Eisenhardt, 1989; Eisenhardt & Graebner, 2007). The data can come from multiple data sources (Yin, 2009). The iterative process does not isolate contexts to ensure the richness of real-world findings (Eisenhardt & Graebner, 2007). The EM is a powerful tool for generating a novel theory (Eisenhardt, 1989) by juxtaposing contradictory or paradoxical evidence (Cameron & Quinn, 1988). The iterative process within an inductive study facilitates constant construct verification (Eisenhardt, 1989).

As a result, the researcher can produce an emergent theory with testable constructs (Eisenhardt, 1989). Furthermore, because the inductive study stays close to actual data during the empirical observation, the resultant theory tends to be empirically valid (Eisenhardt, 1989).

However, there are caveats to using the EM. *First*, empirical evidence can be sophisticated. Due to contextual matters, the data reconciliation of two or more fields can be challenging (Eisenhardt, 1989). This situation happens partially because the number of categories tends to exceed the number of records (Yin, 2009). *Second*, because of the staggering volume of rich data, the final theory can be highly detailed – but not simple (Eisenhardt, 1989). If the theory is not simple enough, it *will* be challenging to generalise it to other fields (Yin, 2009). *Third*, the final theory can be narrow and idiosyncratic. So, the researcher cannot raise the theory's generality (Eisenhardt, 1989). Given EM's advantages and disadvantages, a step-by-step EM is indispensable. Particularly

to assure that the knowledge generation (e.g., emergent theory) can occur as expected.

1.5.2 Research Questions for Empirical Investigation

Every research question is necessary to guide the field studies. A research question explicitly states what researchers intend to understand (Bryman, 2012). It keeps the study focused on specific directions, especially for collecting data. It also helps researchers to manage staggering data volume obtained from empirical work (Bryman, 2012; Eisenhardt, 1989). So, this study applies *problematisation* (Alvesson & Sandberg, 2011) that produces three research questions specific to empirical investigations:

- RQ4. What are the WCDA patterns of action triggered by data availability issues?
- RQ5. What are the WCDA patterns of action triggered by data accuracy issues?
- RQ6. How do employees identify data issues in WCDA?

Furthermore, a unit of analysis defines the focus of the research and is an essential issue (Yin, 2009, p. 29). It is the "who" and "what" of the research (Schwester, 2015). In this case, the unit of analysis can manifest as an individual, event, entity, process, group, or organisation (Baskarada, 2014, p. 4; Yin, 2009, p. 29). The unit of analysis is a scanning device that *can* help the researcher focus during their coding process (data analysis stage). It also supports the researcher in answering empirical research questions (Foss & Waters, 2007).

Table 1.4 shows three research questions and their corresponding unit of observation and analysis. This study employs two units of analysis: workarounds and WCDA (see Figure 1.2). Here, both workarounds and WCDA are naturally attached to the execution of the organisational process (see Figure 1.2). Similarly, WCDA are naturally attached to a workaround (see Figure 1.2). Therefore, this study uses the *organisational process* as the *unit of observation*. Given these relations, this study uses an *embedded unit of analysis* (Yin, 2009).

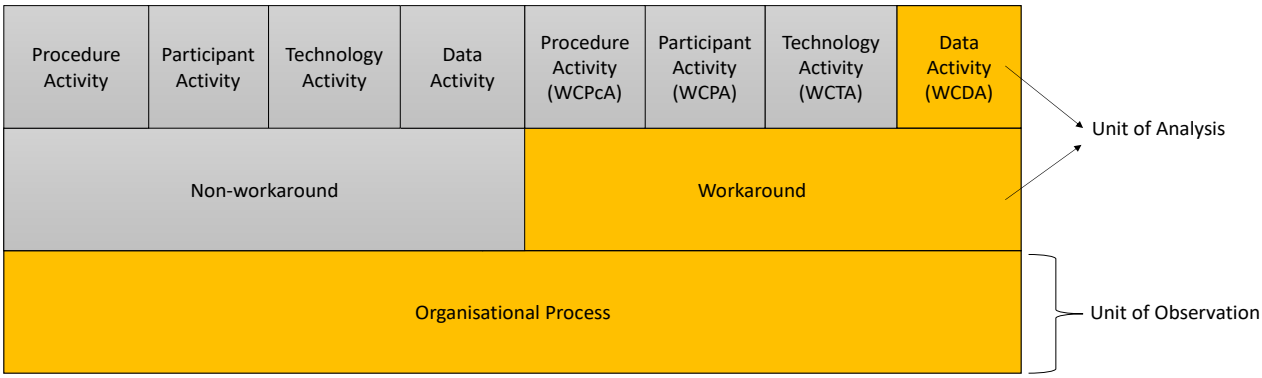

Figure 1.2 Organisational Process and Workarounds

Table 1.4 Research questions and their unit of analysis

RQ	Research Question	Unit of Observation	Unit of Analysis
RQ4.	What are *the WCDA patterns* of action triggered by data availability issues?	Organisational Process	Workarounds
RQ5.	What are *the WCDA patterns* of action triggered by data accuracy issues?	Organisational Process	Workarounds
RQ6.	How do employees *identify data issues* in WCDA?	Organisational Process	WCDA

Determining the organisational process as the observation unit benefits the study for two reasons. First, it allows for finding employees that have the potential to be workaround actors (Wibisono et al., 2020). Second, as these employees are both producers and consumers of the organisational data, they are the best sources to inform any impact of workarounds on data. Hence, as an organisational process is the unit of observation, this study *can* thoroughly examine workarounds.

1.5.3 A Priori Constructs

Eisenhardt (1989) advises that this study can use a priori constructs in executing a field study. A priori constructs are not mandatory for the EM (Eisenhardt, 1989). However, they offer benefits if research uses them. First,

these constructs help shape the emergent theory's initial design (Bryman, 2012; Eisenhardt, 1989). Second, they facilitate the measurement of the construct more accurately later (Eisenhardt, 1989). Third, a priori constructs *can* help researchers organise data to collect and discipline them about what to discover (Bryman, 2012, p. 9). Given these benefits, this research decides to use a priori constructs.

This study obtains the a priori constructs from two literature analyses (Wibisono et al., 2021; Wibisono, Sammon, Heavin, et al., 2022). Generally, there are three groups of a priori constructs: data-related *causes*, data *activities*, and data-related *impacts*. Data-related causes contain the *same constructs* as data-related impacts, such as data loss, data accuracy, data security, data consistency, data access, data presentation, data completeness, data duplication, data meaning, data privacy, and data leak.

Between these two groups, there is another group: data activities. Data activities describe potential data acts that a workaround potentially conceives. For example, employees *enter*, *store*, *transfer*, *retrieve*, *analyse*, *compare*, *manipulate*, *consolidate*, or *transform* data.

On the one hand, research shows that these data activities are the product of data-related causes. For example, because the data are not available in Electronic Health Records, a physician looks for the data on a physical paper (Bozan & Berger, 2018; Flanagan et al., 2013; Saleem et al., 2011).

On the other hand, data activities also facilitate the emergence of data-related impacts. For example, because the physician recorded the data on a mislaid physical paper, the recorded data are lost (Blijleven et al., 2019).

The research investigates the relationships between data issues and the workarounds they create. Therefore, this study focuses on two types of data issues: data availability and data accuracy. These two are the most prevalent data issues from workaround literature (Wibisono, Sammon, Heavin, et al., 2022). Furthermore, the data activities facilitate the emergence of *patterns of action* triggered by these two data issues (e.g., data availability and data accuracy).

Moreover, the use of a priori constructs represents *neither theory nor hypothesis*. These constructs *do not demonstrate associations.* This strategy aligns well with Eisenhardt (1989). She suggests no association among constructs until further field investigation is complete.

This principle helps to be flexible during theorisation processes. It avoids bias and limited findings (Eisenhardt, 1989). Once evidence is found, the association can be *confirmed, revised, disconfirmed,* or even *thrown out* (Eisenhardt, 1989). Besides, EM can reveal why a phenomenon occurs by theorising particular associations (Eisenhardt, 1989). These *underlying causal logics* can construct an acceptable theory (Sutton & Staw, 1995).

1.5.4 Case Selection: Purposive Sampling

This research employs a purposeful sampling strategy (Patton, 2015) to select field studies. There are two logics in this strategy that this research uses: *criterion-based case selection* (Patton, 2015) and *theoretical sampling* (Glaser & Strauss, 1967). Each logic serves different purposes.

On the one hand, the logic of criterion-based case selection is to assess whether the potential field is appropriate. The logic is used while contacting gatekeepers and obtaining their permissions. On the other hand, theoretical sampling logic is used for data collection (after permission is granted). This logic is necessary to establish grounded workaround theories from field studies.

1.5.4.1 Criterion-Based Case Selection

This research uses *Criterion-Based Case Selection* as the logic for the sampling strategy. This logic examines and evaluates all field studies that fulfil some predefined requirements (Patton, 2015). As this research focuses on the workarounds for report production, it selects the *reporting cycles* as the main criterion. If a unit has a frequently required reporting cycle, then the unit is appropriate for selection. As such, it seeks to understand the association between reporting cycles (e.g., short, long) in each unit and their emerging patterns of action.

This understanding is essential because *critical incidents* (Patton, 2015) that trigger workarounds are widely observable in these units. For example, reporting data are *unavailable*, *inaccurate*, *inconsistent*, or *incomplete*. Therefore, employees devise workarounds to address these critical incidents (e.g., fixing these data issues as data brokers) (see Table 1.5). These critical incidents are the focus of criterion sampling for five field studies (e.g., selecting only a unit that contains these incidents).

In addition, a designated "gatekeeper" in each field, such as a unit manager, is responsible for granting permission for field studies. The initial discussions between the researcher and the designated gatekeepers also provide preliminary evidence that helps the researcher determine whether the field selection is compatible with the sampling strategy. Moreover, a summary of the shared characteristics of each case is available as follows (see Table 1.5):

Table 1.5 Shared Characteristics of Field Studies

No	Feature	Characteristic
1	Reporting Cycle	Each field study has a frequent reporting cycle as *required* by upper management
2	Critical Incident	Frequent occurrence (e.g., data unavailable, inaccurate, inconsistent, incomplete)
3	Data Role	Data broker (e.g., not data producer)

In addition, this research completes five field studies in Indonesia (see Table 1.6). It observes units that act as data brokers. They collect data from multiple data providers and serve multiple data consumers (e.g., for reporting purposes) (see Figure 1.3). Data brokers act as intermediaries between data providers, who wish to share their data, and data consumers, who wish to use the available data (Janssen & Singh, 2022). They are an essential component of the data processing ecosystem and manage data in particular ways (Janssen & Singh, 2022).

Table 1.6 Field study in the research

No	Organisation	Site	Reporting Cycle
1	Plantation Company	The Quality Assurance (QA) Unit	Daily
2	Furniture Manufacturer	Administrative Office	Monthly
3	Hospital	Pharmacy Unit	Three monthly
4	University	Academic Office	Six monthly
5	Government agency	Government Bureau	Annually

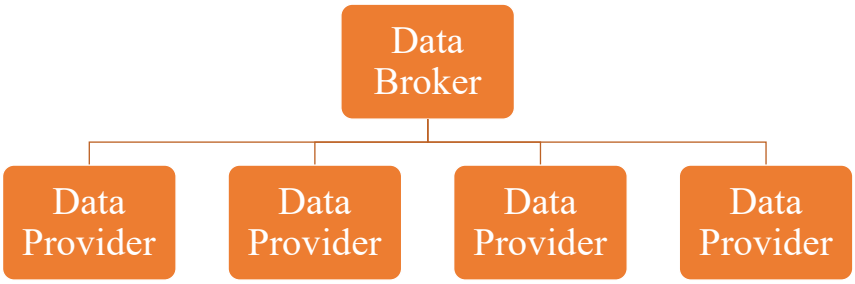

Figure 1.3 The diagram of a data broker and its data providers.

These data brokers must not rely only on formally centralised systems to satisfy data consumers' needs. Infrastructure breakdown, poor system usability, poor system functionalities, and coordination problems are day-to-day events. These events *can* hinder data brokers from meeting data consumers' needs on time. As a result, these data brokers must ensure that the data they collect is "error-free". So, *they execute workarounds*. Hence, these data brokers must deal with various data sources – not only centralised systems. They also check the reliability of the data. So, the produced reports can be insightful and useful for data consumers.

During data collection, this study looks to engage with the following population: *all data broker members*. It must ensure that the population represents operational employees responsible for providing a service to the “data” customer (Alter, 2014).

1.5.4.2 Theoretical Sampling

As part of purposive sampling, theoretical sampling is one logic used for data collection (Glaser & Strauss, 1967) after final permission is given. Theoretically, all field processes (for report production) are sampled for *theoretical reasons* (Eisenhardt & Graebner, 2007). That is, it mandates selecting a highly likely field to produce theories. For example, a researcher does not investigate all field parts (Eisenhardt & Graebner, 2007). Hence, the selection is not random (Bryman, 2012; Glaser & Strauss, 1967). So, another researcher can replicate or extend the emerging theory (Eisenhardt, 1989).

Table 1.7 The Theoretical Sampling Strategy

No	Name	Description
1	Theoretical sampling	Choose a transparently observable process

Eisenhardt (1989) advises three strategies that a researcher can select to achieve theoretical sampling: 1) choose extreme situations, 2) choose polar types, or 3) choose a transparently observable process. Research shows that workaround actors *can* hide workarounds from management and system designers (Drum et al., 2017). Therefore, identifying a workaround can be challenging (Chua et al., 2014; Drum et al., 2017; Zimmermann et al., 2016). Given this fact, this study uses the third option to support theoretical sampling: *choose a transparently observable process* (see Table 1.7).

1.5.5 Collecting Data

The data collection strategy to use is a semi-structured interview. A semi-structured interview helps extract the interviewee's point of interest. Here, the point of interest is the day-to-day practices of the interviewees. All information from the interview becomes the input of the narrative network.

Table 1.8 Potential problems that can emerge during data collection.

No	Problem	Description
P1	No permission	Permissions not granted by management.
P2	No time for an interview	Employees are too busy to give interviews as it is not part of their job responsibilities.
P3	Employees reluctance	Employees fear sharing process experience due to regulatory consequences.
P4	Old project memory	Missing details in the project-based process due to its age.
P5	Blurred outcomes	The unclear outcome complicates the boundary determination of a process to investigate.
P6	Missing employees	The employees undertaking the process are gone (e.g., moved or resigned).
P7	Missing documentation	No documentation available to explain the process
P8	Process duplication	Two or more employees are describing the same process as two separate processes.
P9	Fake process	Employees explain the process that they never undertake
P10	Wrong person	Select the wrong person to ask important questions (e.g., process)
P11	Lack of sensitivity to data issues	Employees may be unaware of data issues due to a lack of sensitivity.
P12	Conflicting data issues	Data issue definitions vary among individuals or groups.
P13	Employees lack ICT	ICT technologies facilitate remote data collection, including email or instant messenger.
P14	Time delay in response	As this study uses ICT tech, participants are not expected to provide an immediate response.

Furthermore, regarding the field's population, this study anticipates that the following problems may occur (see Table 1.8). It needs to collaborate with the unit manager to handle these problems, as they tend to be idiosyncratic. Once all ethical problems are identified, this study assures its ethical considerations.

1.5.6 Ethical Considerations

The researcher obtained ethical approval (ID: Log 2021-052) from the Social Research Ethical Committee (SREC), University College Cork, and followed the approved research protocol, which meets four primary ethics requirements: *information*, *utilisation consent* and *confidentiality*, and (Bryman, 2012).

The ethics principles proposed by Bryman (2012) are practical and achievable. For this study, employees were informed early about the research to meet the *information* requirement. The researcher also ensured that informed *consent* was obtained and that participants were free to withdraw from the research and have their information removed.

The researcher must clarify *how* the research data would be used and who could access it (*utilisation* requirement). The data collection process was explained clearly to all participants, and honest and open communication was established between the author and participants (Sanjari et al., 2014).

Confidentiality was ensured by obtaining participant permission before disclosing their information and anonymising participants and their organisations. All non-digital data was purged to protect anonymity, all audio files were transformed into text, and the original recordings were deleted. Data were processed and stored in the UCC repository to maintain confidentiality.

The *utilisation* requirement suggests that the information gathered was exclusively utilised in the specific inquiry agreed upon by each participant. So, from the author's viewpoint, the study has adhered to research ethics principles.

1.6 Research Roadmap

The roadmap divides the research into three phases: literature review, methodology, and empirical investigation (see Figure 1.4). Each phase facilitates the subsequent phase to materialise. So, these phases work as a chain of action.

1.6.1 Phase 1: Literature Review

This phase includes two literature reviews (Paré et al., 2015) to answer the questions (see Table 1.9). It uses a theoretical review methodology introduced by (Webster & Watson, 2002). These theoretical reviews aim to theorise the taxonomy of WCDI and WCDA from the Information Systems (IS) literature. It uses these two taxonomies to develop a *priori constructs* that are useful to guide the empirical investigation.

1.6.2 Phase 2: Methodology

This stage expands upon the narrative network (Pentland & Feldman, 2007) to support WCDA modelling (as shown in Table 1.9). It establishes WCDA modelling conventions and symbols using the organisational routines theory (Feldman & Pentland, 2003). WCDA modelling assists in identifying the various ways in which WCDA actions are exhibited. It explains how data related to each pattern are created, analysed, and utilised. Additionally, this phase can deduce *patterns of action* that arise from particular data issues.

1.6.3 Phase 3: Empirical Investigation

This phase is the final phase of the research. It empirically examines the reality to understand *patterns of action* produced by data issues. It demonstrates crucial patterns of action to deal with data issues. From these *patterns of action*, it examines a data activity that becomes the common denominator of all identified patterns of action (e.g., evaluate data). So, this phase deepens the further examination by opening the WCDA "evaluate data". In the end, these three phases help to produce research outputs.

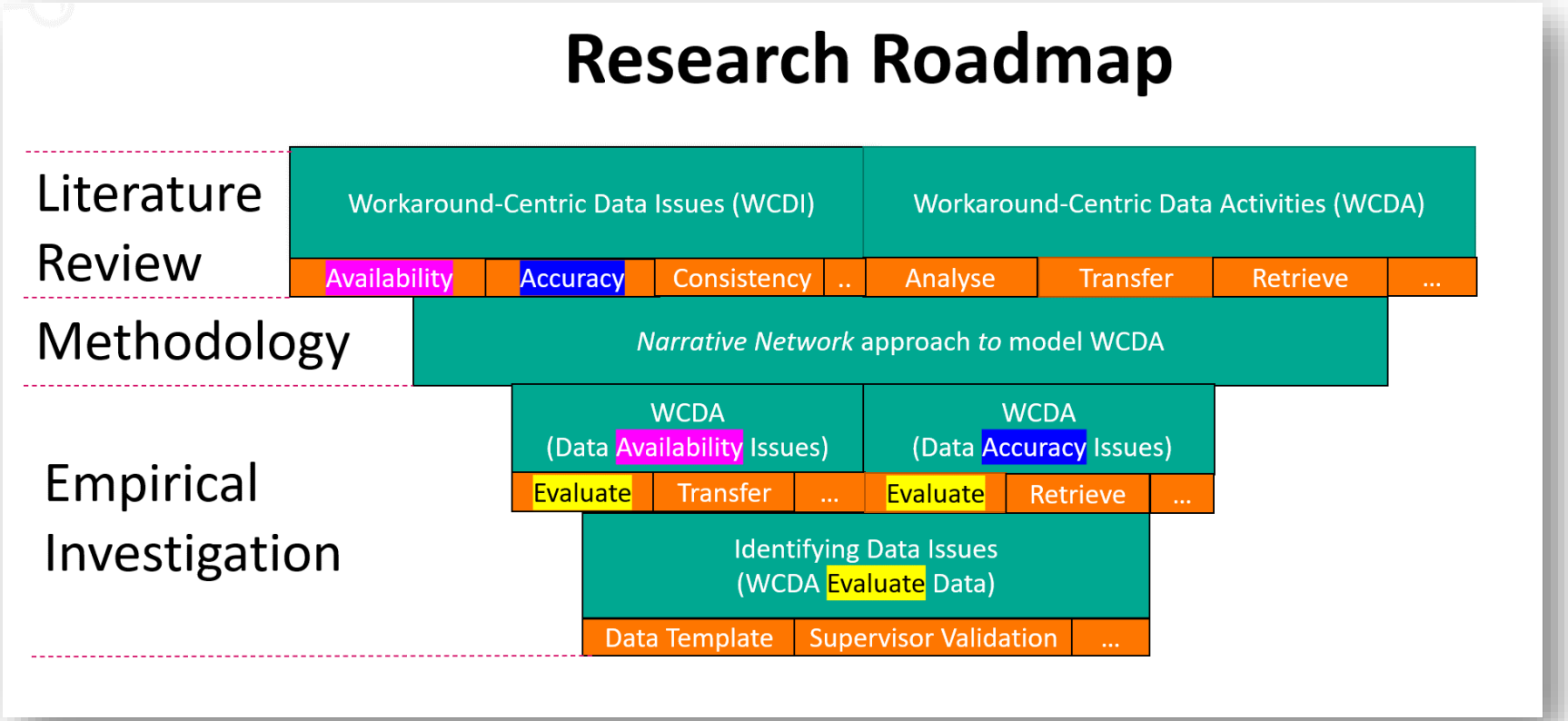

Figure 1.4 Three phases in the research roadmap.

Table 1.9 Three phases, research questions, inputs, and outputs

No	Research Phase	Chapter	Section	Research Question	Input	Output
1	Literature Review	Chapter 2	Section 2.1	RQ1. What are Workaround-Centric Data Issues (WCDI) in organisations?	N.A	Taxonomy of WCDI
2	Literature Review	Chapter 2	Section 2.2	RQ2. What are Workaround-Centric Data Activities (WCDA) in organisations?	N.A	Taxonomy of WCDA
3	Methodology	Chapter 3	Section 3.1	RQ3. How are modelling rules *used* to model WCDA?	*Extended Narrative Network*	*A rule set to model WCDA*
4	Empirical Investigation	Chapter 4	Section 4.1	RQ4. What are *the WCDA patterns* of action triggered by data availability issues?	Taxonomy of WCDI, Taxonomy of WCDA Extended Narrative Network, A rule set to model WCDA	Patterns of Action (Data Availability)
5	Empirical Investigation	Chapter 4	Section 4.2	RQ5. What are *the WCDA patterns* of action triggered by data accuracy issues?	Taxonomy of WCDI, Taxonomy of WCDA Extended Narrative Network, A rule set to model WCDA	Patterns of Action (Data Accuracy)
6	Empirical Investigation	Chapter 4	Section 4.3	RQ6 How do employees *identify data issues* in WCDA?	Patterns of Action (Data Availability), Patterns of Action (Data Accuracy)	The flow diagram of identifying data issues

1.7 Research Output

This study produces nine outputs: five articles have been *published*, one has been *accepted*, and three are *under review*. These outputs encompass conceptual, methodological, and empirical articles. The detail of the outputs is available in Table 1.10.

Table 1.10 PhD project outputs.

No	Title	Type	Status
1	Wibisono, A., Sammon, D., & Heavin, C. (2022). Opening the workaround black box: an organisational routines perspective. IFIP 8.3 Conference. *Journal of Decision Systems*. https://doi.org/https://doi.org/10.1080/12460125.2022.2073647	Conceptual	Published
2	Wibisono, A., Sammon, D., & Heavin, C. (2022). Plausible Pictures for Data Governance: A Narrative Network Approach. *30th European Conference on Information Systems,* https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1109&context=ecis2022_rp	Methodological	Published
3	Wibisono, A., Sammon, D., & Heavin, C. (2022). Data availability issues : decisions as patterns of action. IFIP 8.3 Conference. *Journal of Decision Systems*, 1–14. https://doi.org/10.1080/12460125.2022.2070945	Empirical	Published
4	Modelling data activities in workarounds: a narrative network approach (2020). IFIP 8.3 Conference. *Journal of Decision Systems*, *29* (Sup1), 1–12. https://doi.org/10.1080/12460125.2020.1778874	Methodological	Published

5	Wibisono, A., Sammon, D., Heavin, C., & Alhassan, I. (2022). Theorising Workaround-centric Data Issues: A Literature Analysis. *SSRN Journal.* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4242499	Review	Published
6	Wibisono, A., Sammon, D., & Heavin, C (2021). Enhancing the Theory of Workarounds: Can We Theorise More? *MIS Quarterly Author Development Workshop*	Conceptual	Accepted
7	Wibisono, A., Sammon, D., & Heavin, C. Theorising approaches to identify data issues. *CABS 2 Outlet*	Empirical	Under-Review
8	Wibisono, A., Sammon, D., & Heavin, C. Theorising Workaround-Centric Data Activities in Information Systems Research. *CABS 4 Outlet*	Review	Under-Review *(revise and resubmit)*
9	Wibisono, A., Sammon, D., & Heavin, C. Values-driven workarounds to address data accuracy issues: Theorising from Indonesian field studies. *CABS 3 Outlet*	Empirical	Under-Review

1.8 Conclusion

This chapter provides a short overview of the research. Section 1.2 explains data issues as real-world problems for many organisations. Each organisation must solve these data issues to avoid unintended costs. The motivation for the research highlights an inadequate understanding of the data governance literature regarding these patterns of action. This section explains that the existing workaround literature has many examples of how employees deal with data. So, it has the potential to underpin the theorisation efforts. It problematises the research (Alvesson & Sandberg, 2011; Sandberg & Alvesson, 2011) and guides how this study develops the research questions (see Section 1.3). Section 1.4 explicitly presents the research philosophy pursued

to address the research question. It explains the ontology, empirical focus, type, role of knowledge it produces, type of investigation, and data generation. Also, it considers the relevance of using this philosophy to investigate workarounds. Section 1.5 explains the research plan. Five field studies in Indonesia are selected. These field sites are distinguished by their reporting cycles.

Furthermore, this section explains how data are collected. It indicates that this research uses interviews as the primary data collection method. Also, Section 1.6 shows the research roadmap. First, it develops theoretical models from the literature. Second, the methodological approaches used to visualise (model) WCDA are presented. Third, it empirically examines how organisations deal with data issues (e.g., availability and accuracy). From this information, one data activity found in all identified *patterns of action is examined*– for example, evaluate data. This study evaluates *data* as a black box to understand how employees identify data issues. In the end, Section 1.7 highlights the outputs of this research. There are nine outputs, some of which have been published. These outputs encompass theoretical, methodological, and empirical papers. The following chapter discusses the literature reviews undertaken in this research. Here, it aims to understand workaround-centric data issues and their data activities.

Chapter 2
Literature Review

2.0 Introduction

This chapter aims to develop a priori constructs from the workaround literature. These a priori constructs facilitate the empirical works. This study extracts workaround-centric data issues (WCDI) and workaround-centric data activities (WCDA) from major IS databases (see Table 2.1) to develop the constructs. First, Section 2.1 conducts a comprehensive literature review by identifying 62 empirical papers from Information Systems (IS) databases (2009-2019). Next, it establishes a Taxonomy of WCDI using open coding. Eight data issues that cause workarounds and eleven data issues that workarounds create are presented.

Second, regarding WCDA, Section 2.2 performs a theoretical literature review, identifying 75 empirical articles from Information Systems (IS) databases between 2009 and 2019. It develops a Taxonomy of WCDA using an open coding approach as part of the analysis. Section 2.2 discusses the six most frequent data activities: transfer data, store data, retrieve data, enter data (late), enter data (inaccurate), and analyse data.

These theoretical insights further WCDI and WCDA research and advance the need for more desired behaviours within organisations to tackle the invisible negative impacts of WCDI and WCDA. This study is the first to examine WCDI and WCDA. Hence, it progresses the development of approaches to reduce WCDI's and WCDA's negative impacts.

This chapter informs an empirical investigation of what types of WCDI and WCDA frequently occur in the IS literature. For example, data availability and accuracy are the most frequent data issues in IS literature. Chapter 4 uses these insights to underpin the empirical investigation (see Figure 2.1).

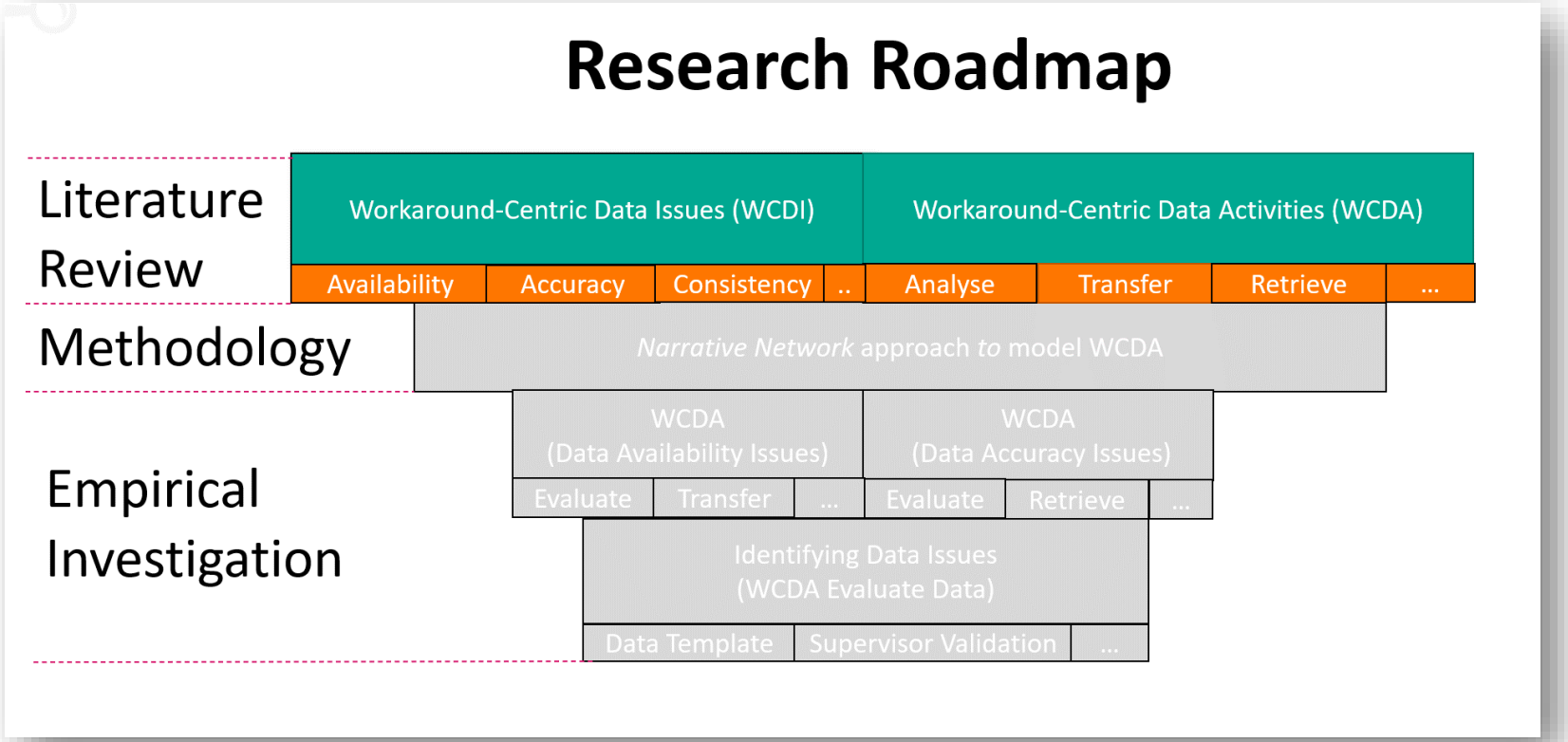

Figure 2.1 Research Roadmap: Literature Review.

Table 2.1 Theorising WCDI and WCDA - Planning Worksheet (Baird, 2021, p. 1207)

Item	Description	Details
Area of theoretical Focus	What theoretical area is being targeted?	This study focuses on extending the *workaround* theory. It develops two taxonomies by theorising certain types of workarounds and their potential data issues and data activities. These are *Workaround-Centric Data Issues (WCDI)* and *Workaround-Centric Data Activities* (WCDA).
Theoretical Backgrounds	What common ground is relevant to this area, your objective, and your target audience?	**Common Ground:** In the workaround literature, this research finds that *a workaround consists of a set of activities* (Haag et al., 2015) and should not be analysed as a single activity (Dunford & Perrigino, 2018). For example, consider an Electronic Health Record (EHR) that does not allow physician collaboration for patient treatment. To solve this collaboration problem, a physician "*copies patient records*" onto a USB drive and *"sends it"* via email (Röder, Wiesche, & Schermann, 2014). So, this workaround consists of *copying* and *sending patient records.* **Research Objective:** the research objective is to answer these some research questions: • What are the data issues that *cause* workarounds? (WCDI) • What are the data issues that workarounds *create*? (WCDI) • What types of workarounds are reported in empirical IS studies? (WCDA) • What are the data activities associated with these types of workarounds? (WCDA) **Target Audience:** The workaround research community
Theoretical Tension	Why is a new theory needed?	**WCDI**

Current workaround literature tends to see data issues as the cause of workarounds (Sillic, 2019; Walterbusch et al., 2017) or that workarounds create (Haag et al., 2018; Stevenson et al., 2018) – not as both. Hence, workaround and data issues are producing vicious cycles.

Understanding these vicious cycles is essential to theorise how a workaround evolves, develops, propagates, and diminishes across units.

WCDA

From the workaround literature, this study finds that a workaround consists of a set of activities – WCDA.

However, in this literature, WCDA are not the focal point of the conversation. As such, workaround researchers tend to see WCDA as somewhat insignificant fragments of a workaround scenario.

They tend to associate WCDA with broader topics such as *compliance and data protection* (cf. Silic et al., 2017; Walters, 2013), *organisation misalignment* (cf. Alraddadi et al., 2018a; Beerepoot & van de Weerd, 2018; Zimmermann & Rentrop, 2014), *coordination* (Davison et al., 2019; Davison & Ou, 2018; Djalali et al., 2015), and *post-adoption satisfaction* (cf. Bozan & Berger, 2018; Khalil et al., 2017).

Hence, WCDA themselves are often overlooked. **So, this is a gap in** understanding **WCDA (knowledge gap).**

Despite the importance of theorising workaround consequences (especially data issues), the current understanding of WCDA remains *embryonic*. For example, what are these activities? What causes them? How are they linked together? After that, it can better assess their impacts.

Resolution of theoretical tension	What is the primary objective of your theory paper	Thus, the primary objective of this research is to **understand WCDI and WCDA**. So, this study inductively builds the *Taxonomy of WCDI.* And a *Taxonomy of WCDA* from the types of workarounds and their data activities.
	What theory building (or extending) approach is applied?	This research uses content analysis and open coding to build the theory to accomplish its objective.
	What is the condition under which you develop your theory?	**Unit of Analysis:** In this case, the unit of analysis is *a set of words*. This study chooses this approach because data activities and their contexts appear in a set of words. Hence, it can better analyse the text by selecting this unit of analysis. **Assumption:** This study assumes that workaround literature has covered WCDI and WCDA to a large extent. But it fails to theorise about WCDI and WCDA. **Other conditions** This research bounds the theorising to a workaround as part of organisational processes. These processes must perceive data as an integral component.
Guidelines (For application)	What steps should future researchers go through when applying for this work?	The following guidelines help future researchers apply this new theory(ising): 1. Capture longitudinal data to understand better how WCDI manifest over time. 2. Collect data from two units (the unit that produces and consumes/uses the data). By doing so, research can understand problematic behaviours relating to entering data, which are often difficult to observe directly (e.g., entering inaccurate or incomplete data).

How can this work be extended?	This theory(ising) can be extended by asking the following research questions: **WCDI: What are the positive impacts of workarounds on data?** For example, are there any impacts on data availability, accuracy, completeness, and consistency? What are they? What specific aspect of workarounds data produce these positive impacts? **WCDA: What are the relationships among WCDA?** WCDA can construct a complex and interdependent web of data activities. Various network analysis parameters such as centrality, density, and cluster can be helpful (Pentland, 1999). For example, centrality can help find the most "important" data activity across a web of data activities. This "important" data activity is now the bottleneck and can stop the critical business process from progressing. Therefore, identifying this "important" data activity can improve the flow of business process execution. As a result, understanding centrality can help organisations size workaround risks from a risk management perspective. Also, it can be beneficial in formulating more effective data governance programmes. **WCDA: How do artefacts (e.g., formal and informal systems) enable and constrain WCDA?** Research shows that artefacts can determine "*what information should be created, selected, and shared, with whom, in which format and in what sequence*" (D'Adderio, 2011, p. 216). Hence, they have a strong connection with data quality. However, the underlying mechanism that links certain WCDA artefacts and data quality is *unclear*. Here, the mechanism must explain "how and why" certain situations and events develop over time, subsequently affecting data quality. This understanding is essential to further inform IT designers to better cope with workaround-aware artefactual analysis, design, testing, deployment, use, and evaluation.

2.1 *Paper* 1: Theorising workaround-centric data issues: a literature analysis

2.1.1 Introduction

This study defines workarounds as "*adaptive processes in centralised system environments*". This definition supports the idea that workarounds can be typical in situations where an IS "*does not meet the requirements of a given task*" (from a user's perspective) (cf. Drum et al., 2016, p. 186). Workarounds are everywhere and can occur anytime (Guerreiro, 2021).

While the impacts of a workaround on an individual user can be favourable (cf. Reiz & Gewald, 2016), the impacts on the organisation overall may be less than desirable. Research shows that if even appreciated in some instances, "*the presence of workarounds is often hidden*" (Drum et al., 2017, p. 48). See Table 2.2 for some examples of workarounds.

Workarounds have received much attention in IS research over the past three decades. However, some workarounds' organisational consequences remain under investigation (Drum et al., 2017; Ejnefjäll & Ågerfalk, 2019; Gozman & Willcocks, 2015; Li et al., 2017; Mallmann, Carlos, et al., 2018). Some examples of organisational consequences include *inferior processes* (Lovett et al., 2013; Reiz & Gewald, 2016; Röder, Wiesche, & Schermann, 2014; Sillic, 2019), *data issues* (Brooks et al., 2015; Drum et al., 2017; Merschbrock & Figueres-Munoz, 2015; Myers et al., 2017), *compliance issues* (Ellingsen et al., 2012; Gozman & Willcocks, 2015; Wolf & Beverungen, 2019), *internal control loss* (Drum et al., 2017; Malaurent & Avison, 2016; Myers et al., 2017), and *organisational inefficiencies* (Fürstenau & Rothe, 2014; Safadi & Faraj, 2010; Ser et al., 2014). Specifically, workaround-centric data issues (WCDI) consequences are the focus of this research.

Table 2.2 Workaround Examples

No	Cause	Workaround	Reference
1	*Data* provided in the formal EHR is *incomplete*	Nurses use paper-based medical records to obtain data	(Ser et al., 2014)
2	Formal Electronic Health Record (EHR) *crashes,* making data unavailable for some time	Nurses use physical paper to record a patient's medical record	(Ibrahim et al., 2019)
3	Enterprise Resource Planning (ERP) is *incapable* of *processing data*	Users develop a spreadsheet processing data ad-hoc	(Ignatiadis & Nandhakumar, 2009)
4	Users do not have access to "fix" wrong data in the formal system	Users develop their version of data in a spreadsheet	(Azad & King, 2012)
5	Users do not find a suitable category in the formal system	Users enter a random category in the formal system	(Van de Weerd et al., 2019)

According to Drum, Pernsteiner, and Revak (2017, p. 44), in integrated enterprise systems environments, "*system users are often unable to fully comprehend their place in the task chain, and thus are unaware of the implications of their actions on information quality.*" Therefore, working around such an integrated enterprise system compounds' *slack data discipline'* and decreases "*integration*" (cf. Drum et al., 2017).

Hence, it is unsurprising that calls have been made in existing research. It further examines workarounds' effect on organisational data (Drum et al., 2016, 2017; Ejnefjäll & Ågerfalk, 2019; McClelland et al., 2004; Myers et al., 2017; Vogelsmeier et al., 2008). Research highlights that data issues *cause*

organisational workarounds (Davison et al., 2019; Malaurent & Avison, 2016; Reiz & Gewald, 2016). Also, workarounds *create* data issues for organisations (Fries et al., 2016; Jagannath et al., 2018; Malaurent & Avison, 2011). As a result, organisations can experience vicious cycles of workaround-centric data issues (*cause* and *create*).

Therefore, this study uses this call for research as a motivation in this literature analysis to explore the relationship between organisational data and workarounds. Specifically, it sets out to answer two research questions to progress theorising around workaround-centric data issues WCDI:

RQ1. What are the data issues that *cause* workarounds?

RQ2. What are the data issues that workarounds *create*?

This section makes two essential contributions. *First*, this research summarises the current theoretical insights regarding WCDI from IS literature by producing a Taxonomy of WCDI. This taxonomy facilitates researchers and managers to identify WCDI in organisations. *Second*, this study shows that specific data issues can produce vicious cycles of workarounds. Therefore, it challenges current workaround literature that sees data issues as the cause of workarounds or that workarounds create – not as both. Understanding these vicious cycles is essential. Particularly to theorise how a workaround evolves, develops, propagates, and diminishes across units. Therefore, this study opens future research in managing workarounds in organisations.

This research arranges the remaining sections as the following. Section 2.1.2 explains the methodology. Section 2.1.3 describes the literature analysis. Section 2.1.4 outlines the findings and presents the discussion. Finally, Section 2.1.5 concludes the research.

2.1.2 Methodology

In line with the research aim, content analysis is a suitable technique commonly employed when scrutinising texts, whether in written or visual form. It proves particularly helpful when the meaning of the text is straightforward and uncomplicated, as noted by Alhassan et al. (2018) and Myers (2009).

Effectively conducting content analysis demands a structured approach to analysis, necessitating the systematic coding of texts by the researcher. Therefore, this study aims to identify structures and patterned regularities within the text by applying a code to each unit of text that seeks to demonstrate its meaning.

Once coded, the resulting output can be both quantified and interpreted. Content analysis is "*a quantitative method of analysing the content of qualitative data*" (Myers, 2009, p. 172). Therefore, to guarantee clarity and transparency in the research process, this study incorporates eight coding steps, as outlined by (Alhassan et al., 2018; Finney & Corbett, 2007). These steps constitute data collection and coding procedures, facilitating a comprehensive and effective analysis.

Step 1. Select the level of analysis.

This step guides the unit of analysis of the study. Finney & Corbett (2007) advise that one can select one of three units of analysis. That is, a single word, a set of words, or an entire document (Finney & Corbett, 2007). In this case, the unit of analysis is a set of words. This research chooses this approach because data issues and their contexts appear in a set of words. Hence, selecting this unit of analysis can better analyse the text.

Step 2: Decide the number of concepts to code for

This step involves deciding whether to use predetermined or emerging concepts (Finney & Corbett, 2007). This study selects emerging concepts inductively during an open coding process. All emerging concepts have something to do with workaround-centric data issues (WCDI) and are later categorised as such. For example, the emerging concepts reveal a data issue that can be categorised (e.g., data availability, data accuracy).

Step 3: Decide whether to code based on concept existence or frequency.

This step determines whether this research codes the emerging concepts based on their existence or frequency (Finney & Corbett, 2007). It uses frequency to facilitate saliency and emphasise discussion (Finney & Corbett,

2007). Coding for frequency allows in-depth insight into emerging concepts and forms a representative picture of WCDI.

Step 4: Decide how to distinguish between concepts.

This step determines whether a concept absorbs another similar concept or not. In this case, this study follows an open coding strategy (Corbin & Strauss, 1990). It classifies what appeared to be similar concepts into a high-level, more abstract concept known as a "category" (Corbin & Strauss, 1990).

Step 5: Develop coding rules.

This step defines specific translation rules to guarantee that the coding procedures remain consistent (cf. Finney & Corbett, 2007). This study establishes and applies the following translation rules during the coding procedure: All articles were first read to code WCDI. It focuses on any words that were associated with "data" or "information" or similar (e.g., "records," "files", "document"). It ensures that these words refer to data issues in a workaround context. Next, it examines the similarities and differences among all the data issues (emerging concepts) and groups these concepts into categories as it finishes coding all articles. This research rechecks all emerging concepts and their meaning in the text. So, it can guarantee that it classifies emerging concepts into the correct category.

Step 6: Filter articles

This step informs what this study must do with un-coded text. It collects 62 relevant articles from 1,024 potential articles (see Figure 2.2). Moreover, it reaches concept saturation (Webster & Watson, 2002) with 62 papers. So, adding more keywords beyond the two used: "workarounds" OR "Shadow IT." is deemed unnecessary. It appreciates that some words can be helpful to replace or complement these two keywords. For example, appropriation, adaptation, retrofitting, reworking, circumventing, inertia, technology change, adapt, refining, improvisation, repurposing, and circumventing (Nevo et al., 2016). This step removes all irrelevant articles. First, it removes non-IS context articles (e.g., health/medical literature). Second, it removes duplicate articles. Third, it removes articles that do not contain data issues. That is, data issues that cause

workarounds and data issues that workarounds create. This investigation discovered that around one-third of these studies focused on Healthcare (13 articles) and Financial (13 articles) (see Figure 2.3)., These figures are followed by Engineering (7 articles) and Education (6 articles). Because some of the workaround studies employ several case study research methods, the total number of domain frequency counts exceeds the number of publications analysed (62 articles)

Step 7: Code the text

This stage utilises the open coding technique established by Corbin and Strauss (1990). Open coding is frequently employed when conducting content analysis (Alhassan et al., 2018; Finney & Corbett, 2007; Goode & Gregor, 2009; Grahlmann et al., 2012). Moreover, the research describes open coding as "*breaking down, examining, comparing, conceptualising, and categorising data*" (Corbin and Strauss, 1990, p. 61). Here, this research extracts nouns that have an association with workaround-centric data. These nouns are adjacent to using the words “data” or “information” in the text. The outcome of this procedure is a list of data issues (concepts). This study also categorises these concepts and develops the categories’ properties and dimensions as part of the open coding approach (Corbin & Strauss, 1990).

Step 8: Analyse the results.

This research evaluates and presents the results (Finney & Corbett, 2007). Frequency is the primary method to illustrate workaround-centric data issues (WCDI). This method enables us to create a taxonomy of WCDI, listing the data issues in order of priority.

2.1.3 Literature Analysis

This study uses open coding to code relevant “workaround-centric data” text across 62 articles. Thus, it infers data issues that: 1) cause workarounds and 2) workarounds create. During the open coding, this research notices that the nouns (e.g., “data” or “information”) are easy to identify in the context of workarounds.

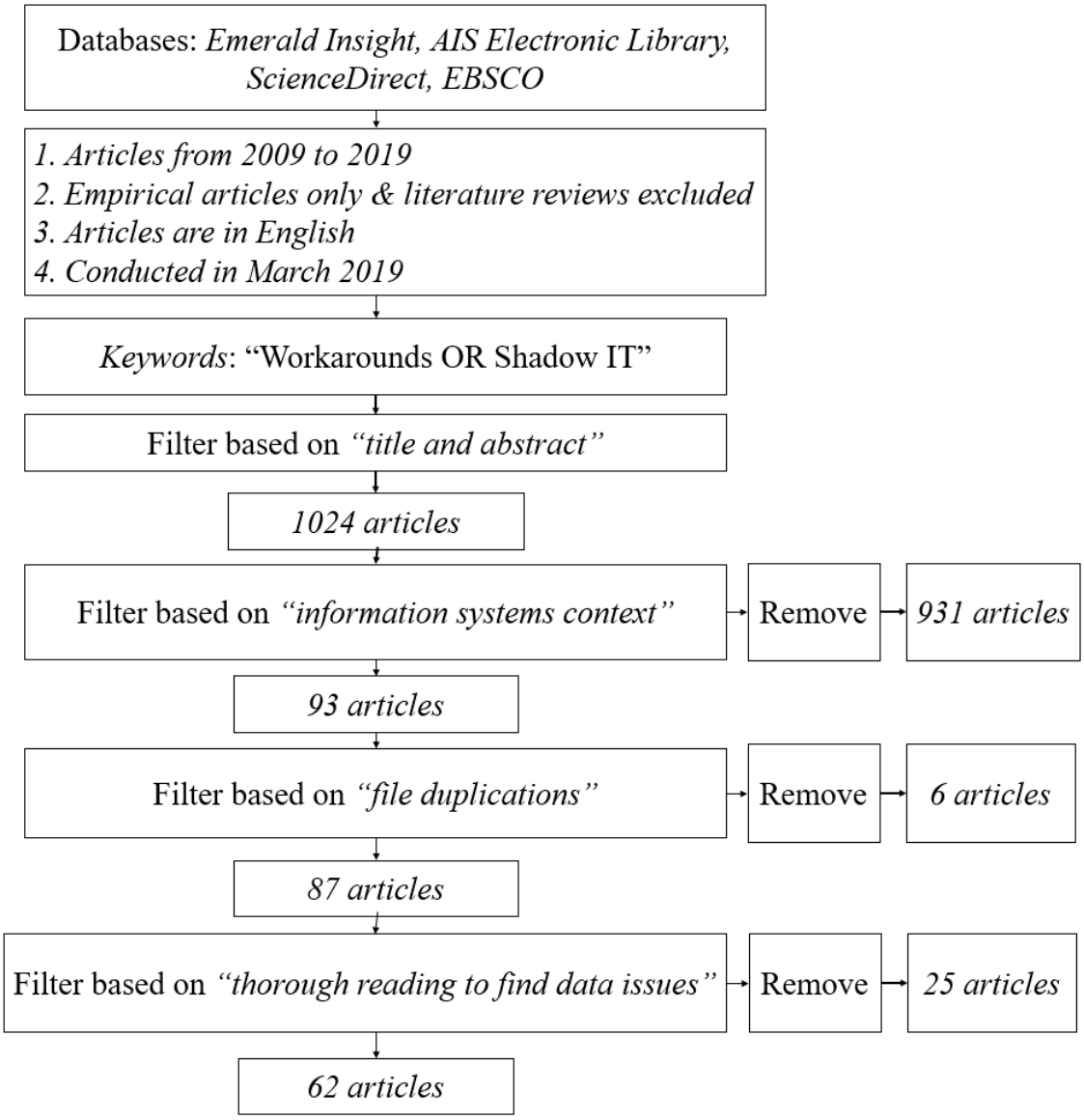

Figure 2.2 Search strategy

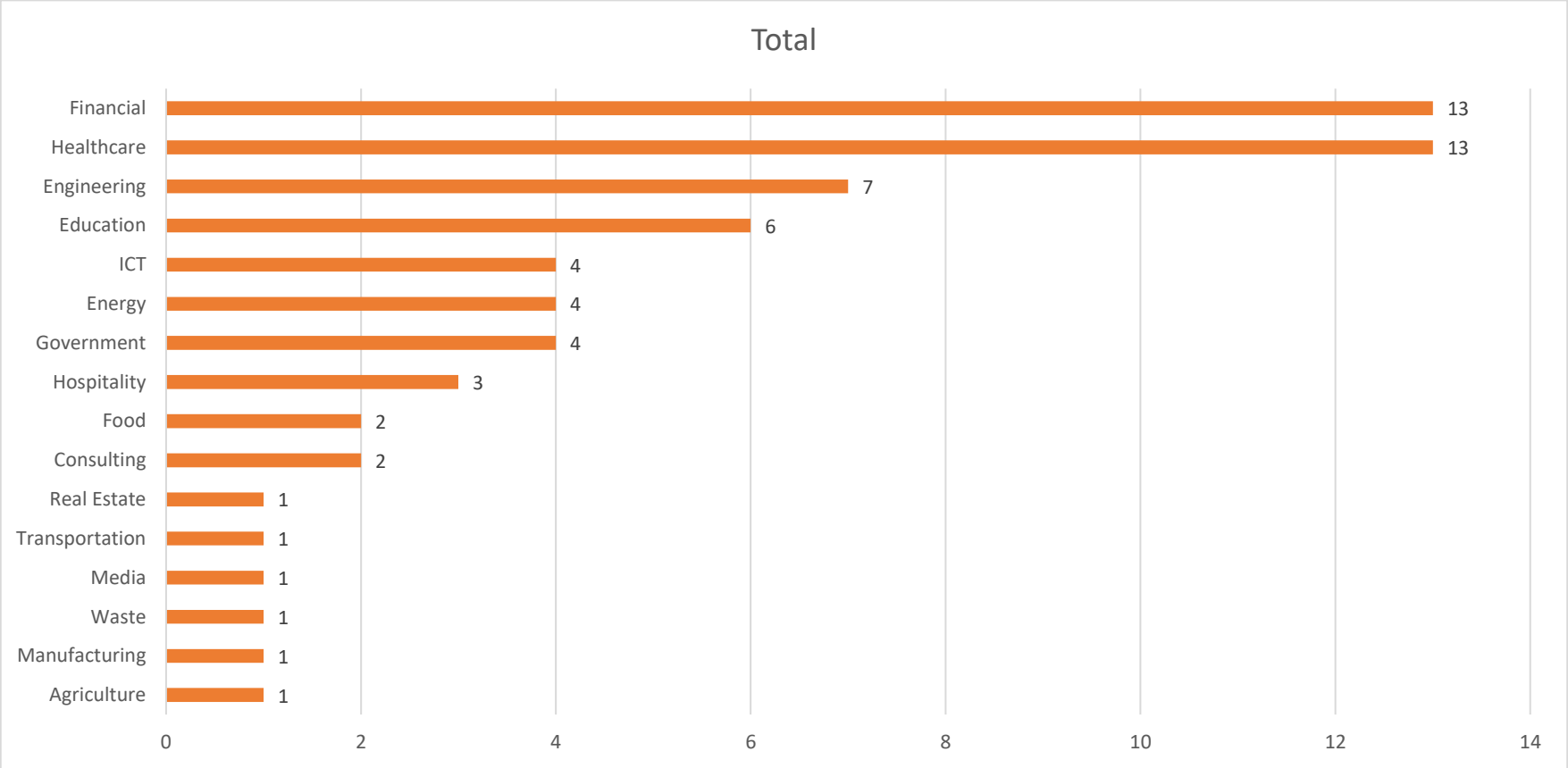

Figure 2.3 Workaround domains where data issues manifest from the IS literature

Table 2.3 Coding examples of data issues

No	Text	Data issues	Cause	Create	Reference
1	"Her reasons to turn to a workaround are the unclear procedure in CIS and doubt that information will not even exist there. She asks for numbers from workers manually and thereafter calculates the figures herself. The social workers respond to the manager's demand with their own workaround: either paper-based or alternative technology-based accountancy."	Data availability	✓		(Huuskonen & Vakkari, 2013, p. 388)
2	"As a simple example, an individual who downloads a tool that contains crypt locker (a malicious software) may unintentionally cause important damage to internal file servers and systems, which can lead to serious consequences such as data availability or downtime."	Data availability		✓	(Sillic, 2019, p. 108)
3	"To get around these limits, the provider altered the reason for the order or the quantity of the medication, even though these alterations led to inaccuracies in the EHR."	Data accuracy		✓	(Flanagan et al., 2013, p. 63)
4	"Secondly, information about a worker in charge was inaccurate in CIS. Inaccuracy was explained by the fact that several workers took care of a child's matters over the client process. Information about a change should have been updated each time, but obviously, that was not necessarily done."	Data accuracy		✓	(Huuskonen & Vakkari, 2013, p. 386)
5	"Electronic workarounds may also improve efficiency and ease of use. However, circumventing EHRs via paper or electronic tools introduces the	Data security		✓	(Kopper et al., 2018, p. 3)

	potential for gaps in documentation and includes other concerns such as information security and authentication of medical orders."				
6	"Such informal systems can damage the quality and security of data through data availability, data duplication, data misuse or inconsistencies."	Data availability, data duplication, data misuse, data consistencies		✓	(Brooks et al., 2015, p. 2)
7	"We are not given a chance to interact with the system. This makes the system chauffeur-driven; we are not in charge of the data. But we are data owners in the agency, and we should administer data entry and queries. The IT department perceives us as computer untrustworthy. So, we 'augmented' the system with our own spreadsheet."	Data access	✓		(Azad & King, 2012, p. 365)
6	"This workaround affected all three stakeholders. First, the clinicians themselves had to maintain two systems by keeping, e.g., patient contact details up to date in both systems. This was considered an additional administrative burden. Second, data stored in the tailor-made database is inaccessible to both internal and external clinicians not working at that specialty."	Data access		✓	(Blijleven et al., 2019, p. 74)

Table 2.4 Workaround-Centric Data Issues and their frequencies

No	Data Issue	RQ1	RQ2
		Cause Workaround	Workaround *Create*
1	Data availability (frequency = 26)	(Bozan & Berger, 2018; Flanagan et al., 2013; Huuskonen & Vakkari, 2013; Merschbrock & Figueres-Munoz, 2015; Niazkhani et al., 2011; Reiz & Gewald, 2016; Safadi & Faraj, 2010; Saleem et al., 2011; Van de Weerd et al., 2019)	(Blijleven et al., 2019; Brooks et al., 2015; Haag & Eckhardt, 2014; Jagannath et al., 2019; Khalil et al., 2017; Sillic, 2019; Walterbusch et al., 2017; Walters, 2013; Zhao et al., 2019)
2	Data accuracy (frequency = 24)	(Azad & King, 2012; Huuskonen & Vakkari, 2013; van den Hooff & Hafkamp, 2017)	(Blijleven et al., 2019; Drum et al., 2015, 2017; Flanagan et al., 2013; Furstenau & Sandner, 2017; Ignatiadis & Nandhakumar, 2009; Jagannath et al., 2018, 2019; Malaurent & Avison, 2016; Myers et al., 2017; Röder, Wiesche, Schermann, et al., 2014; Stevenson et al., 2018; Wolf & Beverungen, 2019)

3	Data security (frequency = 17)	(Saleem et al., 2009)	(Born & Krönung, 2016; Brooks et al., 2015; Gozman & Willcocks, 2015; Györy et al., 2012; Haag et al., 2018; Kopper et al., 2018; Lüker et al., 2016; Mallmann, Carlos, et al., 2018; Myers et al., 2017; Saleem et al., 2011; Walterbusch et al., 2017)
4	Data consistency (frequency = 15)	(Drum et al., 2017; van den Hooff & Hafkamp, 2017)	(Brooks et al., 2015; Drum et al., 2016, 2017; Huuskonen & Vakkari, 2013; Kopper et al., 2018; Li et al., 2017; Myers et al., 2017; Röder, Wiesche, Schermann, et al., 2014; Rubbio et al., 2018; Singh, 2015; Uppatumwichian et al., 2011; Walterbusch et al., 2017; Zimmermann et al., 2017)
5	Data access (frequency = 15)	(Azad & King, 2012; Drum et al., 2015, 2017; Huuskonen & Vakkari, 2013; Spierings et al., 2017; Stevenson et al., 2018; van den Hooff & Hafkamp, 2017)	(Blijleven et al., 2019; Born & Krönung, 2016; Gozman & Willcocks, 2015; Ser et al., 2014; Walters, 2013; Zimmermann et al., 2017)

6	Data presentation (frequency = 15)	(Assis-Hassid et al., 2019; Blijleven et al., 2019; Flanagan et al., 2013; Huuskonen & Vakkari, 2013; Ibrahim et al., 2019; Ignatiadis & Nandhakumar, 2009; Jagannath et al., 2018, 2019; Reiz & Gewald, 2016; Safadi & Faraj, 2010; Saleem et al., 2009, 2011)	(Walters, 2013; Zhao et al., 2019)
7	Data completeness (frequency = 13)	(Huuskonen & Vakkari, 2013; Safadi & Faraj, 2010; Ser et al., 2014)	(Baysari et al., 2018; Beerepoot & van de Weerd, 2018; Drum et al., 2017; Fries et al., 2016; Saleem et al., 2009, 2011)
8	Data duplication (frequency = 26)		(Baysari et al., 2018; Brooks et al., 2015; Huber et al., 2018; Jagannath et al., 2018; Lalley & Malloch, 2010; Mallmann, Carlos, et al., 2018; Stevenson et al., 2018; Walterbusch et al., 2017; Zimmermann et al., 2017)
9	Data meaning (frequency = 9)	(Ignatiadis & Nandhakumar, 2009; Steinhueser et al., 2017)	(Assis-Hassid et al., 2019; Bozan & Berger, 2018; Myers et al., 2017; Saleem et al., 2011;

		Spierings et al., 2017; Walterbusch et al., 2017; Zimmermann et al., 2017)
10	Data privacy (frequency = 9)	(Bozan & Berger, 2018; Burns et al., 2015; Eikey et al., 2015; Khalil et al., 2017; Myers et al., 2017; Röder et al., 2015; Röder, Wiesche, Schermann, et al., 2014)
11	Data leak (frequency = 8)	(Haag & Eckhardt, 2014; Röder, Wiesche, Schermann, et al., 2014; Silic et al., 2017; Silic & Back, 2014; Sillic, 2019; Walterbusch et al., 2017; Walters, 2013)

Those data issues are data accuracy (Blijleven et al., 2019; Flanagan et al., 2013), data consistency (Kopper et al., 2018; Rubbio et al., 2018), data availability (Brooks et al., 2015; Sillic, 2019), and data security (Lüker et al., 2016; Myers et al., 2017). Table 2.3 shows examples of the WCDI coding from the literature.

Based on the analysis of 62 articles, this study finds 8 data issues that cause workarounds. Besides, it identifies 11 data issues that workarounds create (see Table 2.4 and Table 2.5). Hence, workarounds create more data issues than issues that cause workarounds.

This research identifies eight data issues "that cause workarounds" and "that workarounds create". The larger volume of data issues that workarounds create suggests a rationale for introducing a workaround to the working methods. Moreover, the outcome of the workaround execution will most likely reflect an aspect of data use and highlight the potential impacts on the data. Hence, it creates more visible data issues.

Table 2.5 Taxonomy of Workaround-Centric Data Issues (WCDI)

No.	Data Issue	RQ 1	RQ 2	*Total*
		Cause	Create	
1	Data availability	11	15	26
2	Data accuracy	5	19	24
3	Data security	1	16	17
4	Data consistency	2	13	15
5	Data access	9	6	15
6	Data presentation	13	2	15
7	Data completeness	3	10	13
8	Data duplication		11	11
9	Data meaning	2	7	9
10	Data privacy		9	9
11	Data leak		8	8
	Total	46	116	162

Data availability means that "*the intended data are present*" (Kline, 2019, p. 241) from the formal system. For instance, a nurse notes a patient's information on a paper-based record and postpones inputting the data into the EHR (Jagannath et al., 2019). Data availability occurs if the data file goes missing before entering the EHR.

Data accuracy denotes that "*the information is correct*" (NCES, 1997, p. 45). That is, it means that the data accurately represents the real world. For example, if a warehouse stores six items for a specific product, the formal system must show six items in its windows.

Data security is the capability to "*protect data from destructive forces and un-intended actions by unauthorised users*" (Summers, 2004, pp. 4–5). For example, someone injects a virus or creates an attack on the formal system (Akdeniz, 2018).

Data consistency means that "*all clients see the same data*" (Rodger, 2011, p. 180), regardless of where and how these clients access the data. For example, clients with PDAs accessing data from Europe retrieve the same data as American clients retrieving data using a browser on a PC.

Data access denotes "*the ability to retrieve information*" (Garg, 2007, p. 1) from the formal system. For example, the lack of data access happens when the organisation does not allocate proper access to some users (Azad & King, 2012). As a result, these users execute workarounds to complete their work tasks. Furthermore, data security means protecting the data via cryptic measures (Akdeniz, 2018). For example, tokenisation, encryption, and other practices to ensure a system are secure enough (Akdeniz, 2018).

Data presentation relates to the "*design of the client-side display of the data described in the data abstraction*". It deals with user interactions such as user inputs and manipulations of the client-side display performed by the users" (Hu, 2000, p. 464).

Data completeness means the extent of "*the stable data to preserve the information we need*" (Johnston, 2014, p. 278). It means that the fulfilment of each data attribute is complete (not partial) to represent reality. For example, suppose an individual has two attributes in the formal system: name and address. In that case, complete data should fulfil these two attributes.

Data duplication is when finding redundant data on two or more separate files. For example, employees can back up their formal systems data on local databases, spreadsheets, and handwritten notes (Malaurent & Avison, 2011). So, data duplication occurs in the organisation. Employees may do this to avoid data availability due to future system failures (Danilova, 2019; Khalil et al., 2017).

Data privacy means users' right to specify "*when, how, and what information*" they convey to others (Attai, 2018, p. 9). For example, a teacher releases students' marks (what) after the exam (when) on the e-learning system (how). Here, someone compromises the data privacy if there is a mismatch in these three attributes (e.g., when, how, and what).

Data meaning is the original connotation set by the data creator or manipulator of the data. For example, consider the meaning of the term "jaguar." If the creator sets the meaning as a mammal, then the meaning should persist over time. The meaning should not change to "a specific type of car" or "the name of an American tribe".

Data leak means the "*unauthorised transfer of data (or information) from within an organisation to an external destination or recipient*" (Gordon, 2019, pp. 5–6). Data transfer can be electronic and non-electronic (e.g., moving physical devices containing data) (Gordon, 2019). For example, employees copy confidential data to their private USB drives (Silvius & Dols, 2012).

2.1.4 Findings and Discussions

This section outlines the findings based on the 11 workaround-centric data issues extracted from the literature (see Table 2.5). This study presents the six most frequently occurring data issues: data availability, data accuracy, data security, data consistency, data access, and data presentation.

2.1.4.1 Data Availability

Data availability is the most frequently occurring data issue in the literature. It is a situation where data are missing from the organisation's business ecosystems - even though the data was once there. The data availability issue is typically noticeable when users fail to find the data they

require in the formal system (Flanagan et al., 2013; Niazkhani et al., 2011). Users need these data to support their routines (Feldman & Pentland, 2003). Without the data, these routines are impossible to execute.

There is a level of business criticality associated with this data. For example, a tax department needs to collect taxes from its taxpayers. However, some taxpayer records are missing from the enterprise system (Azad & King, 2012). Therefore, the department cannot release official tax bills for missing taxpayers. Given this situation, employees need to execute workarounds. Further, Table 2.5 shows that a workaround can *create* data availability (15), or data availability can *cause* a workaround (11).

This study shows that data availability can materialise in at least four forms. Each form represents a socio-technical situation where data availability can materialise.

First, data availability happens when a user enters data in the wrong location (Baysari et al., 2018; Blijleven et al., 2019; Ignatiadis & Nandhakumar, 2009; Ser et al., 2014). For instance, consider nurses that cannot complete their documentation as the mandatory input field has limited space (Lalley & Malloch, 2010). Consequently, they input the data in an unrelated field. Furthermore, data availability happens when the formal system *provides no category* a user can select to complete a transaction (Safadi & Faraj, 2010; Van de Weerd et al., 2019). Users enter a random category to complete the process (Barrett, 2018). Of course, this random category may be incorrect. Consider a physician failing to find the patient's correct disease category during a patient's treatment in the EHR. As a result, the physician enters the “closest” disease category, even though it is incorrect (Blijleven et al., 2019). Therefore, to address this form of *data availability* data issue, the organisation needs to improve the interaction design (user-friendliness) of the formal system.

Second, data availability happens when an organisation allows one role to enter data on the formal system (e.g., an EHR) on behalf of another user. It usually manifests as a proxy (Bozan & Berger, 2018; Eikey et al., 2015; Röder, Wiesche, & Schermann, 2014). Entering data by proxy is widespread in healthcare (Burns et al., 2015; Saleem et al., 2009; Ser et al., 2014). For example, a physician dictates notes to a nurse while treating patients (Barrett,

2018; Ser et al., 2014). Likewise, a physician uses a personal medical scribe (see this as a proxy) to record patients' data on their behalf during a patient's consultation (Barrett, 2018). The problems lie in how these proxies interpret the physician's words. As sensing and interpretation can be incomplete and inaccurate, the organisation can lose some relevant data (Jagannath et al., 2019). An organisation can implement some strategies to avoid this data availability.

One approach is to have the individual responsible for the transaction (such as the physician) enter the data into the formal system. However, this may not be practical for an organisation, especially in a fast-paced environment like the emergency department. In such cases, an alternative approach is necessary to ensure data availability. For example, proxies can organise a small group discussion involving all team members to verify the completeness and accuracy of the data.

Third, data availability happens when users store data on personal devices. For example, users may store data on notebooks (Van de Weerd et al., 2019) or USB keys (Röder et al., 2015; Röder, Wiesche, & Schermann, 2014; Silvius & Dols, 2012). These devices are vulnerable to theft or malfunction over time. Therefore, the organisation must store data in more reliable storage, such as an authorised cloud service.

Fourth, the formal system provides *no data for decision-making – e.g.,* treating a patient (Niazkhani et al., 2011). The data may be available in the form of scattered paper-based files. Thus, a user requires additional time to collect and process them (Bozan & Berger, 2018). For example, physicians typically create complete patient medical notes using a traditional paper-based approach compared to an EHR (Yang et al., 2012). Some physicians enter "NA" – *not available* – in the mandatory EHR fields to get around the requirement (Yang et al., 2012). The physician does so to complete the transaction, even though the data entered may be incorrect (Yang et al., 2012). Hence, if other users need to capture the updated data, they need to find the paper-based files - where the physician recorded the updated data (Blijleven et al., 2019). There is also a possibility that another user assumes that the data are not present in the system.

This data issue and subsequent workaround practices stem from poor data discipline demonstrated by users (Drum et al., 2016, 2017). The users do not enter the data on time in the formal system (Drum et al., 2017). Thus, the data are unavailable for downstream data users. Therefore, this data issue can cause a workaround with additional data activities, creating further data issues (Drum et al., 2017).

2.1.4.2 Data Accuracy

Data accuracy is the second most frequent data issue in the literature (see Table 2.5). Research shows that data accuracy issues can appear *within the formal system* (Blijleven et al., 2019; Flanagan et al., 2013; Stevenson et al., 2018). These issues happen when users do not accurately capture the transaction (Blijleven et al., 2019). Thus, producing inaccurate data (Ignatiadis & Nandhakumar, 2009). For example, consider a field when a user misleadingly allocates working hours to generate service orders in an ERP (Ignatiadis & Nandhakumar, 2009). The financial clerk must classify an outgoing service order for billing purposes. That is, whether the order is regular work or non-regular work. Regular work refers to any work that involves the maintenance of existing customer contracts. On the other hand, any work beyond the contractual obligations is classified as abnormal work, and the company must invoice it separately.

Despite the importance of such classification, workshop users usually fail to classify incoming work as normal or abnormal (Ignatiadis & Nandhakumar, 2009). Therefore, it leads to data accuracy issues. One can see that data accuracy is inherent to the user's work. So, the organisation needs to enhance the user's working knowledge.

Moreover, research indicates that data availability can produce data accuracy issues in a formal system. For example, missing and outdated data can lead to incorrect automatic invoicing for subsequent users (Wolf & Beverungen, 2019). Consequently, the subsequent users need to fix the data manually. In this case, this manual entry cannot be 100% error-free (e.g., entered data are the updated data, or the calculation mechanism is correct). As a result, this can produce an incorrect invoice for customers (Wolf &

Beverungen, 2019). To solve this problem, the organisation must avoid issues with data availability on its formal system. By doing so, any automatic system that relies on previously entered data can work as it should.

Also, previous studies suggest that *delays* in *entering data* into the formal system can lead to data accuracy issues (Huuskonen & Vakkari, 2013; Stevenson et al., 2018). For example, the nurse *delays entering data* to treat patients or to complete a more urgent task (Stevenson et al., 2018)., In the delay, a nurse can make a mistake regarding the data (Stevenson et al., 2018). For instance, because the nurse delays entering data, they can forget some parts of the data. Therefore, they may enter data *inaccurately* (Lovett et al., 2013; Yang et al., 2012) or *incompletely* (Beerepoot & van de Weerd, 2018; Reiz & Gewald, 2016). Hence, to solve this problem, the organisation needs to enhance the users' discipline around entering data on time in the formal system.

2.1.4.3 Data Security

The third data issue is data security. It is the ability to "*protect data from any destructive forces and un-intended actions by unauthorised users*" (Summers, 2004, pp. 4–5). For instance, users store their data on an untrusted cloud service to support their daily work (Chua et al., 2014; Khalil et al., 2017; Mallmann, Maçada, et al., 2018; Wolf & Beverungen, 2019). Consequently, this user has unintentionally exposed organisational data to another party – which may be an unauthorised party (e.g., a cloud service provider). This unauthorised party can access the data beyond the organisation's awareness and endanger the data accordingly (e.g., corrupt or sell the data). Once it happens, data security is compromised.

As shown in the previous example, users are responsible for data security (Silic & Back, 2014; Walterbusch et al., 2017). Even so, these users may not be aware that their actions compromise the organisation's data security. Hence, users' continuous security awareness is indispensable in solving this action. To maintain data security awareness, the organisation must deliver regular training and education for its members (Silic & Back, 2014). By doing so, the organisation can improve data security in its ecosystems for extended periods.

In a similar vein, a data security issue can *cause* a workaround. For example, a user executes a paper-based workaround to avoid perceived data security issues in the EHR by printing the data on a paper-based file (Saleem et al., 2009). Later on, the user sends the file elsewhere (Saleem et al., 2009). Even though the user has good intentions, printing data on a paper-based file can produce other data issues (e.g., data availability). For this reason, regular security awareness training and education are mandatory for all organisations. By doing so, the user can avoid such unnecessary actions.

2.1.4.4 Data Consistency

The fourth data issue is data consistency. It can occur due to the mismatch between the *logic of work* and the data presented in the formal system (Drum et al., 2016; Huuskonen & Vakkari, 2013). Consequently, the system fails to demonstrate consistent business logic (Myers et al., 2017). For example, consider material master data in an ERP (Drum et al., 2016). There are two types of material master data for each product, in this case: raw goods and finished goods. However, tribal or informal knowledge is required to classify a product into the appropriate category (Drum et al., 2016). An issue arises when the employee who organises the global database's product does not possess this tribal knowledge. So, the employee can mistakenly assign raw goods as finished goods in the ERP. Therefore, these raw goods are recorded and appear as finished goods in the ERP.

Consequently, data consistency issues arise because employees use multiple data sources. Unlike the manufacturing people who create the product physically, the IT staff in the manufacturing unit cannot record these transactions in the ERP - because raw goods are assigned as finished goods (Drum et al., 2016). This situation causes downstream users to find an alternative explanation for disputed product-related data in the ERP. For example, employees find a situation where a product exists in the warehouse (while the organisation never procured or manufactured the product). So, they try to reconcile them (Drum et al., 2017). That is because the work logic between raw and finished goods differs in manufacturing. Hence, it affects the accounting process. These actions can be burdensome and time-consuming for

users, mainly when dealing with global master data (Li et al., 2017). An organisation needs to enhance user working knowledge to tackle data consistency issues.

2.1.4.5 Data Access

The fifth data issue is data access. This study understands data access as "the ability to retrieve information" (Garg, 2007, p. 1). Research shows that the unnecessary allocation of user access contributes to data access issues (Azad & King, 2012; Zimmermann et al., 2017). For example, a hospital applies permission management to allocate specific data access to groups of health professionals (Koppel et al., 2015). This situation is especially relevant to non-permanent workers (e.g., senior house officer - SHO). In one example, a hospital limits an SHO's access to the hospital system and patient data for thirty days. There may cause an SHO to consult with clinicians and nurses about patients beyond this period. The SHO has no access to the EHR (Koppel et al., 2015). This situation can result in permanent staff sharing their usernames and passwords with the SHO. Hence, they can access the system and reassess the patient's condition (Koppel et al., 2015).

The organisation must allocate appropriate access to all health professionals to solve these data access issues. That is, depending on the roles and responsibilities of each health professional. Also, a timing issue arises around the time required to complete a patient case. As illustrated in this example, a single case may run beyond the terms of an employment contract.

2.1.4.6 Data Presentation

The sixth and final data issue is data presentation. It occurs when users are dissatisfied with how the formal system presents the data (Ignatiadis & Nandhakumar, 2009; Saleem et al., 2011). So, users execute workarounds to solve this issue. For example, physicians have difficulty finding a specific chunk of patient data because the system displays too much unnecessary data (Reiz & Gewald, 2016). Therefore, they ask the patient to find the required data (Flanagan et al., 2013; Reiz & Gewald, 2016). Because of this issue, a user (e.g., a physician) can rely on paper-based files – not a formal system (Saleem

et al., 2011). Here, the paper-based files present the data in a more accessible and effective manner. So, the physician does not necessarily need to experience unnecessary scrolling down to find data (Saleem et al., 2011).

Even though users frequently use paper-based files, these files have limitations, such as minimal space to store the required data. These files are just cognitive artefacts to memorise the most critical data for daily operations – not all data (Assis-Hassid et al., 2019; Saleem et al., 2009; Ser et al., 2014). Hence, the users arrange the data presented in these artefacts to satisfy their needs. Thus, for better user-friendliness to enhance data presentation issues, the formal system can adopt these cognitive artefacts to visualise their data.

The following section presents the conclusions of the work. It explores the critical lessons learned, the theoretical and managerial implications of the analysis, the limitations of the research, and the future research directions.

2.1.5 Conclusion

Rowe advocates that "*the quality of a literature review depends on its systematicity since systematicity implies reproducibility through documenting the search process and potentially indicates comprehensiveness*" (Rowe, 2014, p. 246). Following Rowe, this study gathers and examines 62 published IS articles. Using a systematic approach by the eight coding steps of content analysis, the selection process yielded 1,024 articles for further selection and exclusion criteria, leading to the exclusion of 937 articles. After a more in-depth review of the remaining 87 articles, 62 are found to serve the research purpose explicitly. These 62 articles were analysed using open coding to complete an in-depth content analysis of WCDI. Hence, this research can ensure the reproducibility of the work by other researchers.

2.1.5.1 Key Lessons Learned and Implications

This section reflects on the literature review's lessons learned and theoretical implications. In addressing the first research question, this study finds 8 data issues that *cause* workarounds (see Table 2.5). Further, it addresses the second research question and finds 11 data issues that workarounds *create* (see Table 2.5). Some data issues are unique to "cause workarounds" or

"workarounds create". Ten data issues (including the six most frequently occurring) are associated with both (see Table 2.5). These data issues are problematic because they can introduce workaround cycles. First, they can *cause* a workaround, creating another data issue. Second, this data issue can trigger another workaround. Therefore, the multiplicative effect of these data issues can be more significant, and their impact (be it positive or negative) can be more significant over time within an organisation. As a result, this research **challenges** the waterfall-style logic of the widely-cited Theory of Workarounds (Alter, 2014) by highlighting these multiplicative effects extracted from the literature.

The Theory of Workarounds explains the genesis of a workaround in chronological order. It appreciates that a workaround can have *"local and broader consequences"* (Alter, 2014, p. 1055). However, it fails to appreciate that some consequences (e.g., *data issues*) can cause further workarounds. These consequences may create further data issues. They produce a vicious cycle. This vicious cycle can potentially go unappreciated within an organisational setting. Therefore, understanding this cyclical characteristic can allow theorising *workaround evolution* within specific contexts. Therefore, it discourages an overly simplified view of a workaround. This viewpoint aligns with the *theory of organisational routines* (Feldman & Pentland, 2003; Pentland & Feldman, 2005). Over time, this viewpoint requires observation and analysis to appreciate the intricate genealogy of a workaround and the associated data activities and data issues.

Moreover, this study expects that some data issues (e.g., *data availability* and *data accuracy*) strongly affect certain constructs (e.g., *user* and *data entry*). For example, this study finds that *data availability* is the most complex issue due to its prevalence. To mitigate against data availability, managers should focus on *user-friendliness*, *data entry*, *data storage*, and the *user*. Furthermore, this research finds that focusing only on the user can address many data issues, such as data accuracy, consistency, access, and availability. Focusing on the *user* to alleviate workarounds aligns with the institutionalised workarounds model (cf. Azad & King, 2012). This model suggests that an employee's work ethos is the factor that causes workarounds (Azad & King,

2012, p. 369). For example, work ethos determines an employee's data discipline and working knowledge. Indeed, individuals' *ignorance* (Malaurent & Avison, 2016), individuals' *habits* (Zimmermann & Rentrop, 2014), and individuals' *judgment* (Silic et al., 2017) are linked to the existence of workarounds.

Based on the analysis, *data availability* and *accuracy* are the two most prominent WCDI. Both data issues can have a significant impact on an organisation. Indeed, throughout the current global pandemic, this study has seen the importance of *data accuracy* (e.g., a review of how Public Health England calculated COVID-19 death figures saw the UK's COVID-19 death toll reduced by more than 5,000). *Data availability* (e.g., employees storing sensitive company data on USB drives to enable remote working from home) is equal. Therefore, *data availability* and *accuracy* may alter the perception of the creative practices using organisational data (workaround-centric data activities) to complete work-related tasks. Unfortunately, ongoing commentaries suggest that data are suffering from being seen as a "bi-product" of the input and output activities performed on the various business applications. Thereby remaining a "*second-class business resource*" (Laney, 2018). However, "*inertia in organisations can kill attempts to achieve more with data*" (Carruthers & Jackson, 2018, p. 2).

So, to address WCDI, an organisation needs to manage, at all levels, to cultivate an appreciation of the deliverable data value from their formal IS. This action can help to avoid the need for workarounds where their impact harms organisational data.

2.1.5.2 Limitations and Future Research Directions

Rowe (2014) indicates that the IS community needs to produce more literature reviews. He argues that "*every researcher looks for [a literature review] when starting a research study*" and "*literature reviews can be highly valuable*" (Rowe, 2014, p. 242). Therefore, the primary goal of a literature review is "*to classify what has been produced by the literature*" (Rowe, 2014, p. 243). So, this study believes that it has achieved this goal for WCDI 1) cause workarounds and 2) workarounds create (see Table 2.5)

This research is the first to analyse WCDI in the IS domain. However, it appreciates that it has only presented a detailed commentary on the six most frequently observed data issues. WCDI can be complicated and challenging to identify, interpret, and codify when the perspectives of multiple stakeholders are taken on board. For example, to complete a sales order, a salesperson may need to provide five attributes: a customer's name, address, products, price, and quantity sold. So, if the salesperson can access these five attributes, the salesperson may think that no data issue materialises. However, a financial analyst may need to know the agreed discount and billing method to complete the sales order. If these two data attributes are absent, the financial analyst may think that a data completeness data issue exists.

This data issue may cause a workaround. The finance analyst combines these two data attributes with the salesperson's dataset, creating a new dataset. This data activity can create another data issue (data duplication). While WCDA can often involve the creation of a new dataset (copy of the originals), the practice can create data issues ("*endless heartburn for CSOs and CDOs*") (Laney, 2018)). Conversely, WCDA can also afford "opportunities" (Laney, 2018) to generate more value from the data. Where this section focuses on data issues (negative impacts of workarounds), further research can examine the positive impacts of workarounds (data opportunities). WCDI may not be directly observable as and when they happen. For example, consider a user that enters data inaccurately or incompletely (Flanagan et al., 2013; Huuskonen & Vakkari, 2013). These data issues cannot be observable unless other users use the data in the system at a future time. These issues can never be uncovered if no other user uses this data. Therefore, this research suggests collecting workaround data over an extended period (longitudinally). By doing so, these researchers can capture workarounds and their data issues comprehensively. This action ensures the documentation of a complete picture of WCDI.

To conclude, this research incorporates the recommendation of Webster and Watson (2002, p. xxi). So, it has delivered the contributions (what is new?), impact (so what?), logic (why so?), and thoroughness (well done?) expected from a review article. This study expects this work to represent a "benchmark for others."

2.2 *Paper* 2: Theorising workaround-centric data activities in information systems research

2.2.1 Introduction

Data issues (e.g., data inaccuracy, data loss, data breach, data leak) can cost an organisation billions of dollars annually (Caulkins et al., 2007; Powell et al., 2008; Teo & Tan, 1997). These issues can be the product of workarounds and their associated data activities. This study characterises these activities as Workaround-Centric Data Activities (WCDA). For example, a hospital employee stored data on an informal system connected to the Internet. Thus, the protected health information of 6,800 patients was illegally available on Google. Consequently, the New York-based hospital was fined $4.8 million for HIPAA violations due to data leakage (Silic et al., 2017). As this example suggests, workarounds are often "*non-standard procedures operators devise to compensate for system deficiencies*" (Courtright et al., 1998, p. 1150). This definition facilitates the notion that workarounds can be a typical behaviour where an IS "*does not meet the requirements of a given task*" (from a user's viewpoint) (Drum et al., 2016, p. 186).

Consider an Electronic Health Record (EHR) that does not allow a collaborative approach among physicians during patient treatment. To solve this collaboration problem, a physician "*copies patient records*" and "*sends them*" via email (Röder, Wiesche, & Schermann, 2014, p. 5). Here, copying data and sending data are examples of WCDA. Because most workarounds are typically untested and experimental, "*the costs of workarounds are hard to measure*" (Röder et al., 2015, p. 482). For instance, what if a patient's data are misplaced or misused? In that case, this situation leads to a data breach and a data loss, resulting in prohibitive costs for the organisation (Röder, Wiesche, Schermann, et al., 2014). Therefore, understanding WCDA is extremely important, with a solid relevance to practice. This study needs to increase the theorising to address such "*real-world problems of practitioners*" (Moeini et al., 2019, p. 198).

Moreover, even though existing literature frequently considers WCDA, they are not the focal point of the conversation and are often overlooked. As such, workaround researchers tend to associate WCDA with broader topics such as compliance and data protection (cf. Silic et al., 2017; Walters, 2013), organisation misalignment (cf. Alraddadi et al., 2018a; Beerepoot & van de Weerd, 2018; Zimmermann & Rentrop, 2014), coordination (Davison et al., 2019; Davison & Ou, 2018; Djalali et al., 2015), and post-adoption satisfaction (cf. Bozan & Berger, 2018; Khalil et al., 2017). Subsequently, despite the importance of theorising workaround consequences (especially data issues), the current understanding of WCDA remains embryonic. For example, what are these activities? What causes them? After that, this study can better assess their impacts.

Furthermore, theorising WCDA also addresses a research call by Ejnefjäll & Ågerfalk (2019). They indicate that a workaround is a complex phenomenon but, for the "*most part, surprisingly under-investigated and [under] theorised*" (2019, p. 341). Therefore, as WCDA lacks appropriate theorising, a theoretical review (cf. Paré et al., 2015) is relevant and vital for the IS community. Given these reasons, Section 2.2 aims to investigate WCDA by posing two research questions:

RQ1. What types of workarounds are reported in empirical IS studies?

RQ2. What are the data activities associated with these types of workarounds?

This study summarises the theoretical insights of WCDA from IS research, captured in the Taxonomy of WCDA (see Table 2.9). This taxonomy is beneficial for academia and practitioners to position the understanding of WCDA in organisational contexts. It contributes to the workaround literature by providing WCDA taxonomy. As to practical implications, the theoretical insights highlight the data activities associated with workarounds. This increased visibility of WCDA can raise practitioners' awareness of this often-invisible phenomenon. All too often, WCDA leads to the emergence of Workaround-Centric Data Issues (WCDI), which can be costly. WCDA

visibility can also inform the design of data policies that better reflect the desired behaviours. Mainly to ensure that organisational data are treated as a strategic business asset. By doing so, organisations are better placed to formulate effective and sustainable data governance programmes (especially given the existence of workarounds and their associated data activities).

The remaining sections are as follows: Section 2.2.2 explains the methodology, Section 2.2.3 describes the literature analysis, and Section 2.2.4 presents the findings and discussion. Lastly, Section 2.2.5 concludes the study.

2.2.2 Methodology

Since this study aims to gain an in-depth understanding of WCDA, content analysis is deemed appropriate. Content analysis is frequently used when analysing text (written or visual sources). It is useful when the meaning of the text is relatively straightforward and obvious (cf. Alhassan et al., 2018; Myers, 2009). A structured approach to analysis is pivotal in conducting content analysis. So, this approach requires the researcher to code the texts systematically.

Moreover, by searching for "structures and patterned regularities in the text" (cf. Myers, 2009), the researcher applies a code to a unit of text that seeks to demonstrate the meaning of that text. Once coded, the resulting output can be both quantified and interpreted. Therefore, content analysis is "*a quantitative method of analysing the content of qualitative data*" (Myers, 2009, p. 172). This research uses eight coding steps (cf. Alhassan et al., 2018; Finney & Corbett, 2007) to inform the data collection and coding procedures. These steps enable researchers to ensure clarity and transparency in the processes undertaken. The steps and associated decisions are as follows:

Step 1. Select the level of analysis.

This step guides the unit of analysis of this study. Finney & Corbett (2007) advises that one can select one out of three units of analysis. That is, a single word, a set of words, or an entire document (Finney & Corbett, 2007). In this case, the unit of analysis is a set of words. It chooses this approach

because data activities and their contexts appear in a set of words. Hence, selecting this unit of analysis can better analyse the text.

Step 2: Decide the number of concepts to code for

This step involves deciding whether this study used predetermined or emerging concepts (Finney & Corbett, 2007). It selects emerging concepts coded inductively during an open coding process. All emerging concepts have to do with WCDA and were later categorised. For example, the emerging concepts reveal a data activity categorised as entering and storing data.

Step 3: Decide whether to code based on concept existence or frequency.

This step determined whether to code the emerging concepts based on their existence or frequency (Finney & Corbett, 2007). This research uses frequency to analyse saliency and emphasis (Finney & Corbett, 2007). Coding for frequency obtains an in-depth insight into emerging concepts. It forms a representative picture of WCDA.

Step 4: Decide how to distinguish between concepts.

This step determines whether a concept absorbs another similar concept or not. It follows an open coding strategy (Corbin & Strauss, 1990). It classifies similar concepts into a high-level, more abstract concept known as a "category" (Corbin & Strauss, 1990).

Step 5: Develop coding rules.

This step defines specific translation rules to ensure the consistency of the coding procedures (cf. Finney & Corbett, 2007). This study establishes the following translation rules and applies them during the coding procedure:

First, all articles are read to code WCDA. For types of workarounds, it captured sentences containing underpinning "artefacts" where data activities occur. For example, "*one sends data using email*" or "*enters data incompletely in the ERP system*". Here, email and ERP systems are two artefacts emerging from the text. It also captures sentences that contain an imperative verb and data as an object. For example, store data, transfer data and enter data.

Second, this research focuses on words that were associated with "data" or "information" or similar (e.g., "records," "files", "document"). It ensures that these words refer to data activities in a workaround context.

Third, it examines the similarities and differences among all the data activities (emerging concepts). By doing so, these concepts can be grouped into categories. Once coded, every article, all emerging concepts, and their meaning in the text are re-checked. This study guarantees that it classifies emerging concepts into the appropriate category.

Step 6: Filter articles

This step Informs what this study must do with uncoded text. It collects 75 relevant articles from 1,024 potential articles (see Figure 2.4). Moreover, this research reaches *concept saturation* (Webster & Watson, 2002) with 75 articles. Therefore, adding more keywords beyond the two used: "workarounds" OR "shadow IT." is unnecessary. It appreciates that some words can be helpful to replace or complement these two keywords. For example, *appropriation, adaptation, retrofitting, reworking, circumventing, inertia, technology change, adapt, refining, improvisation, repurposing, and circumventing* (Nevo et al., 2016).

During this step, this research removes all irrelevant articles. First, it removes articles that have no IS context. It included several articles focused on the health/medical domain, which were not directly relevant to this IS research. Second, it removes duplicate articles. Third, it removes articles that do not contain data activities.

In categorising these 75 articles (see Figure 2.5), this study finds that one-third of the workaround research focused on Healthcare (24 articles). This figure is followed by Financial (18 articles) and Government (9 articles). Given that some of the workaround studies use multiple case study research designs, the number of domain frequency counts totals more than the number of articles reviewed (75 articles)

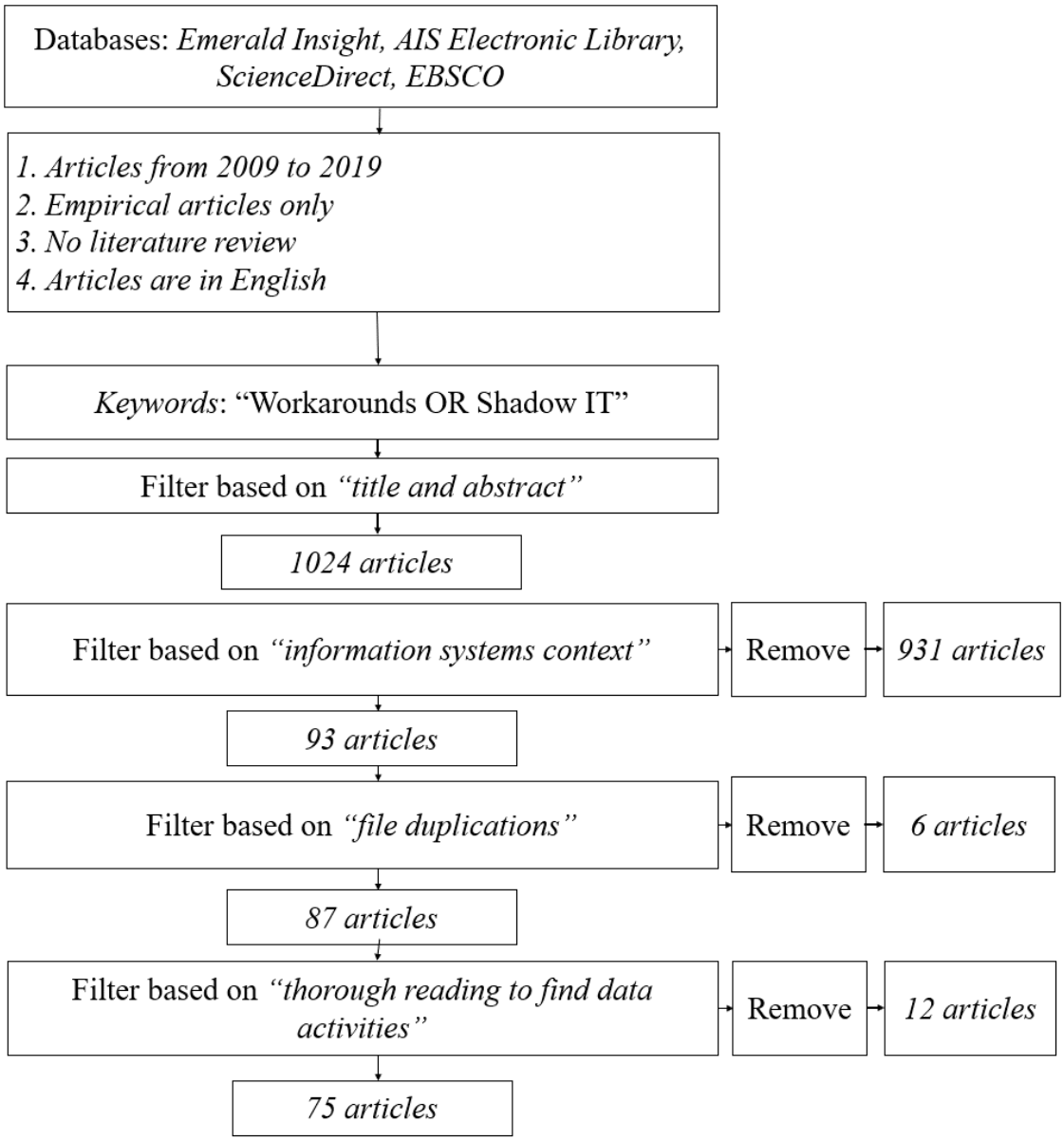

Figure 2.4 Search strategy

.

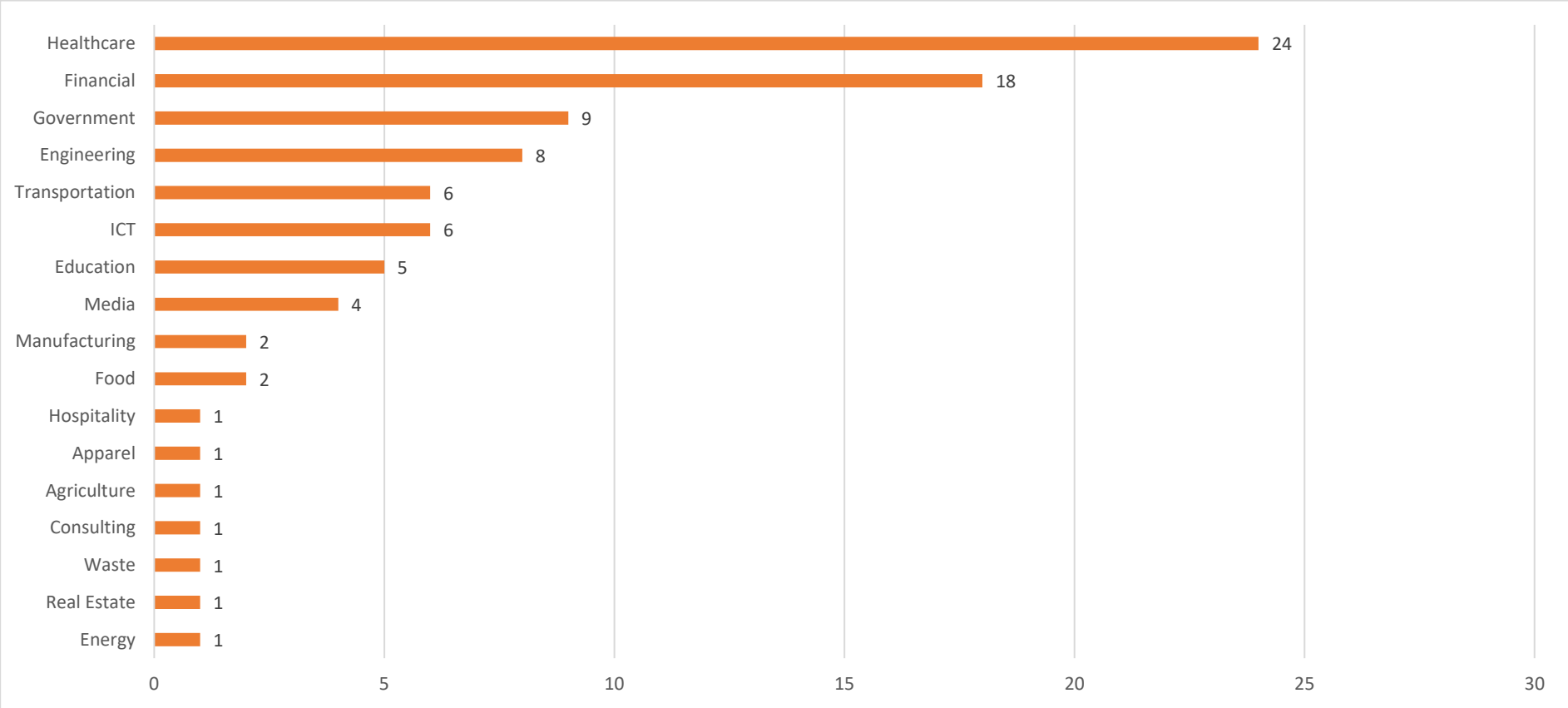

Figure 2.5 Workaround domains where data activities manifest from the IS literature.

Step 7: Code the text

This step applies the open coding approach (Corbin & Strauss, 1990). Open coding is widely applicable in conducting content analysis (Alhassan et al., 2018; Finney & Corbett, 2007; Goode & Gregor, 2009; Grahlmann et al., 2012). Moreover, the research describes open coding as "breaking down, examining, comparing, conceptualising, and categorising data" (Corbin and Strauss, 1990, p. 61).

Open coding enables the revealing of hidden concepts from the text. In this case, there are two stages. *First*, this research examines each article and looks for types of workarounds. *Second*, for each type of workaround, this research searches for the imperative verbs (Alhassan et al., 2018) associated with each type of workaround. These imperative verbs have something to do with data. For example, there is an excerpt, "However, physicians copy patient records onto USB sticks or send it via email" (Röder, Wiesche, & Schermann, 2014, p. 5). In this case, "copy" and "send" are two imperative verbs that relate to data. The outcome of this procedure is a list of data activities (concepts). This step also categorises these concepts (types of workarounds and data activities). Further, it develops the categories' properties and them dimensions as part of the open coding approach (Corbin & Strauss, 1990).

Step 8: Analyse the results.

This step evaluates and presents the results (Finney & Corbett, 2007). It uses frequency as the primary method to show types of workarounds and WCDA. This method enables us to create a Taxonomy of WCDA, listing the data activities in order of priority. Table 2.8 shows the operational definition of each data activity, which facilitates the analysis. The analysis reveals 14 data activities across the three types of workarounds (see Table 2.9). Generally, data activities in the formal system are more homogenous than in other categories. Here, the majority are associated with entering data. However, this step carefully classifies each imperative verb by its context to avoid misclassification. For example, it discovers that one can classify "create data" into three meanings. That is, analysing data, manipulating data, and storing data.

Table 2.6. Coding examples of types of workarounds and their data activities

No	Text	Artefact	Workaround type	Data Activity	Reference
1	"A healthcare provider uses a file transfer app on a personal device to transfer unencrypted patient records from a hospital computer to a personal computer to review patient treatment plans at home."	IS	Informal system use	Transfer Data	(Burns et al., 2015, p. 148)
2	"I store or transport documents (considered to contain sensitive/confidential information) on portable storage like a USB stick."	USB Stick	Informal system use	Store data, Transfer data	(Silvius & Dols, 2012, p. 6)
3	"When W20 occurs, team managers systematically avoid the use of the application and write and share their reports via Google Drive instead."	Google Drive	Informal system use	Store data. Transfer data	(Davison et al., 2019)
4	"Users may create workarounds. For example, they may access information from a legacy system or paper records."	Legacy system, Paper	Informal system use	Retrieve data	(Bozan & Berger, 2018)
5	"Examining a patient and entering this data in the EHR after the patient consultation session. "	EHR	Formal system use	Enter data (late)	(Blijleven et al., 2019, p. 74)

6	"He identified three concrete forms of workarounds. Firstly, the data are adjusted, or even incorrect data are entered to get the desired outcome in IS"	IS	Formal system use	Enter data (inaccurately)	(Huuskonen & Vakkari, 2013, p. 381)
7	"Doctors were dictating notes and leaving data entry to administrative staff."	(No artefact)	Human-proxy use	Enter data (delegated)	(Ser et al., 2014, p. 3)
8	"An example of such a workaround in healthcare is a nurse writing information about patients on paper instead of using the portable Computer on Wheels (COW)."	Paper	Informal system use	Store data	(Beerepoot & van de Weerd, 2018, p. 1)
9	"Workarounds addressing the inflexibility of standardised ERP often involve importing and exporting data to and from Microsoft Excel, where data can be further analysed and consolidated."	ERP, Spreadsheet	Informal system use	Import data, export data, analyse data, consolidate data	(Davison et al., 2019)

Therefore, this step determines the classification based on the context of the imperative verb. For example, when the verb is associated with making a report, it codifies it as analysing data (cf. Davison et al., 2019; Drum et al., 2015). When the verb is associated with editing a record in an existing file, this step codifies it as manipulating data (cf. Silic & Back, 2014). When the verb is associated with making a new file or record (which previously did not exist), this step codifies it as storing data (cf. Van de Weerd et al., 2019).

2.2.3 Literature Analysis

For the literature analysis, this section adopts an iterative, open coding approach (see step 7). The analysis reveals several types of workarounds and their associated data activities. It also provides insights into the artefacts used in the workarounds (see Table 2.6). For example, artefacts include the following: formal Electronic Health Records – *69 concepts found* (Barrett, 2018; Stevenson et al., 2018), private cloud services – *37 concepts found* (cf. Haag & Eckhardt, 2014; Silvius & Dols, 2012; Wolf & Beverungen, 2019), formal Enterprise Resource Planning systems – *29 concepts found* (cf. Alraddadi et al., 2018a; Huber et al., 2018; Myers et al., 2017), private email – *13 concepts found* (Davison et al., 2019; Van de Weerd et al., 2019; Wolf & Beverungen, 2019), and private USB drives – *6 concepts found* (cf. Haag et al., 2018; Röder et al., 2015).

From the analysis, this research can categorise all workarounds into three types: *informal, formal,* and *human proxy use* (see Table 2.7). Table 2.7 presents the coded frequency of each of the workaround types. This categorisation also captures the answer to the first research question.

Informal system use is the unauthorised utilisation of an artefact to complete a task. The artefact encompasses software, spreadsheets, cloud services, physical paper, and personal devices. A workaround actor may incorporate more than one artefact to accomplish their goal. For example, one uses a spreadsheet to store data and then transfers the spreadsheet via email to colleagues (Davison et al., 2019; Ignatiadis & Nandhakumar, 2009).

Table 2.7 Types of workarounds and their frequencies

Workaround	Reference
Informal system use (frequency = 221)	(Azad & King, 2012; Barrett, 2018; Beerepoot & van de Weerd, 2018; Blijleven et al., 2019; Born & Krönung, 2016; Bozan & Berger, 2018; Burns et al., 2015; Chua et al., 2014; Davison et al., 2019; Djalali et al., 2015; Drum et al., 2015, 2017; Eikey et al., 2015; Ellingsen et al., 2012; Fürstenau et al., 2016; Fürstenau & Rothe, 2014; Furstenau & Sandner, 2017; Gozman & Willcocks, 2015; Haag et al., 2018; Haag & Eckhardt, 2014; Huber et al., 2018; Ibrahim et al., 2019; Ignatiadis & Nandhakumar, 2009; Jagannath et al., 2018; Khalil et al., 2017; Kopper et al., 2018; Li et al., 2017; Mallmann, Carlos, et al., 2018; Mallmann, Maçada, et al., 2018; Merschbrock & Figueres-Munoz, 2015; Myers et al., 2017; Niazkhani et al., 2011; Reiz & Gewald, 2016; Röder et al., 2015; Röder, Wiesche, & Schermann, 2014; Röder, Wiesche, Schermann, et al., 2014; Saleem et al., 2009, 2011; Ser et al., 2014; Sillic, 2019; Silvius & Dols, 2012; Singh, 2015; Spierings et al., 2017; Steinhueser et al., 2017; Stevenson et al., 2018; Uppatumwichian et al., 2011; Van de Weerd et al., 2019; van den Hooff & Hafkamp, 2017; Walterbusch et al., 2017; Wolf & Beverungen, 2019; Yang et al., 2012; Zamani et al., 2013; Zimmermann et al., 2017)
Formal system use (frequency =169)	(Barrett, 2018; Baysari et al., 2018; Beerepoot & van de Weerd, 2018; Burns et al., 2015; Drum et al., 2015, 2017; Eikey et al., 2015; Ibrahim et al., 2019; Ignatiadis & Nandhakumar, 2009; Ilie, 2013; Lalley & Malloch, 2010; Lovett et al., 2013; Malaurent & Avison, 2016; Reiz & Gewald, 2016; Röder, Wiesche, & Schermann, 2014; Safadi & Faraj, 2010; Saleem et al., 2009; Ser et al., 2014;

	Stevenson et al., 2018; Van de Weerd et al., 2019; van den Hooff & Hafkamp, 2017; Vassilakopoulou et al., 2012; Yang et al., 2012)
Human proxy use (frequency =18)	(Beerepoot & van de Weerd, 2018; Burns et al., 2015; Eikey et al., 2015; Reiz & Gewald, 2016; Saleem et al., 2009; Ser et al., 2014; Wolf & Beverungen, 2019)

Formal system use is the unanticipated use of the formal system. This behaviour occurs when an employee is innovative in using the formal system. This innovation is often beyond a system designer's prescription (Alter, 2014; Drum et al., 2015; Koppel et al., 2008). Therefore, it is viewed as a workaround, even though an employee directly engages with the formal system. As a workaround, formal system use can also produce data issues. For example, an employee enters data in the wrong place, e.g., via a free text notes field, instead of selecting from a pre-populated drop-down list (Baysari et al., 2018). Hence, the data are technically "gone", and navigating the formal system cannot guarantee retrieval. Therefore, the formal system cannot provide the data for future business insights.

Human proxy use is when an employee delegates a task to another individual to complete it on their behalf. It can be a meditated action in an organisation. It can directly associate with formal or informal system use or no association. Human proxy use is prevalent in healthcare (cf. Burns et al., 2015; cf. Reiz & Gewald, 2016). For example, a physician uses a medical scribe to enter data into the EHR. The physician takes care of the consultation session with a patient. Consequently, the medical scribe may miss some mandatory information due to mishearing. As a result, the data are now missing from the formal system.

Table 2.8 Operational Definition of Workaround-Centric Data Activities

No	Data Activity	Description	References
1	Enter data - Late	Delaying entering data into the formal system – e.g., do other things first, enter data later.	(Alraddadi et al., 2018a; Assis-Hassid et al., 2019; Barrett, 2018; Beerepoot & van de Weerd, 2018; Behrens, 2009; Blijleven et al., 2019; Davison et al., 2019; Flanagan et al., 2013; Furstenau & Sandner, 2017; Ibrahim et al., 2019; Jagannath et al., 2018, 2019; Safadi & Faraj, 2010; Saleem et al., 2009, 2011; Ser et al., 2014; Stevenson et al., 2018; Uppatumwichian et al., 2011; Van de Weerd et al., 2019; van den Hooff & Hafkamp, 2017; Vassilakopoulou et al., 2012)
2	Enter data - Inaccurate	Entering inaccurate data into the formal system.	(Blijleven et al., 2019; Drum et al., 2015, 2017; Flanagan et al., 2013; Huuskonen & Vakkari, 2013; Lovett et al., 2013; Malaurent & Avison, 2016; Reiz & Gewald, 2016; Röder, Wiesche, & Schermann, 2014; Van de Weerd et al., 2019; Yang et al., 2012)
3	Enter data – No Entry	Not entering data at all.	(Beerepoot & van de Weerd, 2018; Blijleven et al., 2019; Drum et al., 2017; Ibrahim et al., 2019; Jagannath et al., 2019; Reiz & Gewald, 2016; van den Hooff & Hafkamp, 2017; Vassilakopoulou et al., 2012)

4	Enter data – Incorrect (location)	Using the wrong feature in the formal system to enter data, e.g., the employee uses an open text field to enter data instead of using a mandatory combo box.	(Barrett, 2018; Baysari et al., 2018; Blijleven et al., 2019; Ignatiadis & Nandhakumar, 2009; Ilie, 2013; Lalley & Malloch, 2010; Ser et al., 2014)
5	Enter data – Incomplete	Entering limited information about an event.	(Drum et al., 2017; Reiz & Gewald, 2016; Stevenson et al., 2018; Van de Weerd et al., 2019; Yang et al., 2012)
6	Enter data - Delegated	Delegating their tasks to someone else – e.g., a doctor asks a nurse to enter data on behalf of the doctor.	(Barrett, 2018; Burns et al., 2015; Eikey et al., 2015; Jagannath et al., 2019; Saleem et al., 2009; Ser et al., 2014)
7	Transfer data	Transmitting data from one system to another system – at least one of the systems is an informal system.	(Assis-Hassid et al., 2019; Blijleven et al., 2019; Born & Krönung, 2016; Davison et al., 2019; Djalali et al., 2015; Drum et al., 2016; Furstenau & Sandner, 2017; Gozman & Willcocks, 2015; Haag & Eckhardt, 2014; Huber et al., 2018; Ibrahim et al., 2019; Kopper et al., 2018; Li et al., 2017; Mallmann, Carlos, et al., 2018; Mallmann, Maçada, et al., 2018; Merschbrock & Figueres-Munoz, 2015; Röder, Wiesche, Schermann, et al., 2014; Sillic, 2019; Silvius & Dols, 2012; Uppatumwichian et al., 2011; Van de Weerd et al., 2019; Wolf & Beverungen, 2019)

8	Store data	Putting data in an informal system.	(Assis-Hassid et al., 2019; Barrett, 2018; Blijleven et al., 2019; Burns et al., 2015; Djalali et al., 2015; Drum et al., 2016, 2017; Eikey et al., 2015; Flanagan et al., 2013; Ibrahim et al., 2019; Jagannath et al., 2019; Khalil et al., 2017; Mallmann, Carlos, et al., 2018; Mallmann, Maçada, et al., 2018; Röder et al., 2015; Röder, Wiesche, & Schermann, 2014; Silic et al., 2017; Steinhueser et al., 2017; Stevenson et al., 2018; Wolf & Beverungen, 2019)
9	Retrieve data	Collecting data from a single or multiple data sources.	(Bozan & Berger, 2018; Chua et al., 2014; Flanagan et al., 2013; Huuskonen & Vakkari, 2013; Li et al., 2017; Mallmann, Carlos, et al., 2018; Reiz & Gewald, 2016; Röder, Wiesche, Schermann, et al., 2014; Rubbio et al., 2018; Spierings et al., 2017; Steinhueser et al., 2017; Van de Weerd et al., 2019; Walterbusch et al., 2017; Wolf & Beverungen, 2019; Zhao et al., 2019)
10	Analyse data	Examining data for interpreting and explaining the data	(Blijleven et al., 2019; Burns et al., 2015; Davison et al., 2019; Drum et al., 2015, 2016; Flanagan et al., 2013; Huuskonen & Vakkari, 2013; Ignatiadis & Nandhakumar, 2009; Moss & Berner, 2015; Niazkhani et al., 2011; Röder et al., 2015; Röder, Wiesche,

			& Schermann, 2014; Uppatumwichian et al., 2011; Van de Weerd et al., 2019)
11	Compare data	Tracking, checking and matching data to find the most updated and reliable data among data sources	(Ellingsen et al., 2012; Li et al., 2017; Niazkhani et al., 2011; Saleem et al., 2011; Singh, 2015; Uppatumwichian et al., 2011; Van de Weerd et al., 2019; van den Hooff & Hafkamp, 2017)
12	Manipulate data	Making changes to the data (e.g., editing the data, updating the data)	(Furstenau & Sandner, 2017; Ignatiadis & Nandhakumar, 2009; Mallmann, Maçada, et al., 2018; Silic & Back, 2014; Sillic, 2019; Uppatumwichian et al., 2011)
13	Consolidate data	Merging data from multiple data sources	(Davison et al., 2019; Drum et al., 2015; Sillic, 2019; Wolf & Beverungen, 2019; Zimmermann et al., 2017)
14	Transform data	Converting the format of data from one format to another format – usually to enter data into another system	(Davison et al., 2019; Djalali et al., 2015; Haag et al., 2015, 2018; Mallmann, Maçada, et al., 2018)

Table 2.9 Taxonomy of WCDA

			RQ2. Workaround-Centric Data Activities														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	
			Enter data														
			Late	Inaccurate	No Enter	Incorrect (location)	Incomplete	Delegated	Transfer data	Store data	Retrieve data	Analyse data	Compare data	Manipulate data	Consolidate data	Transform data	*Total*
RQ1. Types of Workarounds	1	Informal system use							70	62	44	16	12	7	5	5	221
	2	Formal system use	36	22	13	11	7										169
	3	Human proxy use						7			7	3	1				18
Total			96						70	62	51	19	13	7	5	5	

This study analyses the text in the collection of 75 articles. It finds imperative verbs related to data activities. For example, *analyse* (Burns et al., 2015; Davison et al., 2019), *compare* (cf. Li et al., 2017; cf. Uppatumwichian et al., 2011), *consolidate* (Davison et al., 2019; Zimmermann et al., 2017), *manipulate* (cf. Furstenau & Sandner, 2017; cf. Huber et al., 2018), retrieve (cf. Ser et al., 2014; cf. Van de Weerd et al., 2019), *store* (cf. Jagannath et al., 2018), *transfer* (cf. Burns et al., 2015; Kopper et al., 2018), and *transform* data (cf. Mallmann, Maçada, et al., 2018).

Table 2.8 shows the operational definition of each data activity, which facilitates the analysis. The analysis reveals 14 data activities across the three types of workarounds (see Table 2.9). Generally, data activities in the formal system are more homogenous than in other categories. Here, the majority are associated with entering data. However, this study carefully classifies each imperative verb according to its context to avoid misclassification. For example, it discovers that one can classify "create data" into three meanings. That is, analysing data, manipulating data, and storing data.

Therefore, this research determines the classification based on the context of the imperative verb. For example, when the verb is associated with making a report, it codifies the verb as analysing data (Davison et al., 2019; Drum et al., 2015). When the verb is associated with editing a record in an existing file, it codifies the verb as manipulating data (cf. Silic & Back, 2014). When the verb is associated with making a new file or record (which previously did not exist), it codifies the verb as storing data (cf. Van de Weerd et al., 2019).

2.2.4 Findings and Discussion

This section elaborates on the findings from the literature analysis. In answering Research Question 2, it uncovers 14 data activities across three types of workarounds. It presents a detailed account of the most frequently occurring data activities (see Table 2.9)

Following the Pareto Principle, this study selects data activities that cover at least 80% of all occurrences. This Pareto Principle indicates that 80% of consequences originate from 20% of causes. So, by capturing 80% of data activity occurrences, this study covers a substantial amount of WCDA.

Therefore, the theorising efforts are representative. The following section presents six data activities (see Table 2.9), namely: transfer data (70), store data (62), retrieve data (51), enter data - late (36), enter data – inaccurate (22), and analyse data (19).

2.2.4.1 Transfer Data

Transferring data is the most frequent data activity identified in the literature (70 concepts). As such, this research defines transferring data as one consciously copying data from an informal system to another informal system (41 coded instances). It also includes a formal system to an informal system (24 coded instances). All is to complete a task (see Table 2.10). For example, a physician copies confidential patient data from the EHR onto a USB Stick for further use at home (Röder, Wiesche, & Schermann, 2014). Also, they send the data to a physician colleague to collect medical opinions (Röder, Wiesche, & Schermann, 2014). Several data issues can arise as an employee transfers data from a formal/informal system to an informal one. Possible issues are *data privacy* (Röder, Wiesche, Schermann, et al., 2014) and *data leak* (Haag & Eckhardt, 2014; Röder, Wiesche, Schermann, et al., 2014). These data issues can present severe risks for an organisation, including legal issues (e.g., GDPR) around data ownership.

The analysis indicates that most data transfer (the first type) occurs from an informal system to an informal one (see Table 2.10). Workarounds in this type encompass transferring data using collaborative technologies. For example, *Dropbox* (cf. Born & Krönung, 2016; Chua et al., 2014; Sillic, 2019) or *Google Drive* (cf. Born & Krönung, 2016; Mallmann, Carlos, et al., 2018; Van de Weerd et al., 2019).

The second type of data transfer is from a formal system to an informal one (see Table 2.10). In this type, an employee downloads data from the formal system (e.g., EHR, ERP) and transfers it into private storage (cf. Röder et al., 2015; Silvius & Dols, 2012), physical paper (cf. Assis-Hassid et al., 2019), or spreadsheets (Davison et al., 2019; Li et al., 2017).

The third type of data transfer is from an informal system to a formal one (see Table 2.10). For example, an employee can process data on physical

paper (cf. Ibrahim et al., 2019), an unrecognised application (cf. Furstenau & Sandner, 2017), or a spreadsheet (Davison et al., 2019). Later, the processed data are imported back into the formal system. Research also shows that the processed data in informal systems may not be checked for accuracy (Furstenau & Sandner, 2017).

Table 2.10 Distribution of Transferring Data in the Literature

		TO		**TOTAL**
		Formal System	Informal System	
FROM	Formal System	1	24	25
	Informal System	5	40	45
	TOTAL	6	65	70

The fourth type of transferring data is from a formal system to a formal system (see Table 2.11). For instance, data entry to an EHR may be complex (see Table 2.11). So, an employee can copy data from previous progress notes in the EHR form and paste them onto the new EHR form (Blijleven et al., 2019). The new entry may not be accurate because the employee may not check their data entry.

Moreover, research shows that there are two main reasons underpinning data transfer. They are *aligning one's job* with co-workers (cf. Burns et al., 2015; Mallmann, Carlos, et al., 2018; Silvius & Dols, 2012) and *sharing knowledge* among peers (cf. Mallmann, Carlos, et al., 2018). As this behaviour is mainly driven by the need to communicate, organisations require reliable and responsive formal communication tools for employees.

Further, research indicates that poor usability can trigger an employee to transfer data elsewhere (cf. Assis-Hassid et al., 2019; Blijleven et al., 2019; Röder, Wiesche, & Schermann, 2014; Steinhueser et al., 2017). For example, a standardised template for EHR data entry can be extensive. Therefore, employees copy & paste patient data from previous progress notes (cf. Blijleven et al., 2019). By copying & pasting, the employee can complete their task while overcoming the challenging ergonomic design of the formal system.

Table 2.11 Coding example of Transferring Data

NO	Text	FROM		TO		References	Workaround Cause		
		Formal system	Informal system	Formal system	Informal system		Ergonomic Design	Communication Features	Functionality
1	"For example, the EHR study offers an extensive standardized data entry template for entering patient data. However, because of the perceived low usability of the standardized data entry template, all users preferred copy-pasting most patient data from previous progress notes into a new progress note."	✓		✓		(Blijleven et al., 2019, p. 73)	✓		

2	"The information that I have in handwriting, I write down all the morning labs based on what I see on the EHR. I do this by hand because it is easier for me to process the information when I'm writing that for myself."	✓			✓	(Assis-Hassid et al., 2019, p. 7)	✓		
3	"One of its more popular functions (one that shadows the functionality of the central system) is the uploading of students' end-of-term results into the Enterprise System."		✓	✓		(Behrens, 2009, p. 124)			✓
4	"I1 uses Facebook and LinkedIn as work tools, mainly to look for clients' information. The information collected is shared with co-workers via WhatsApp using a personal smartphone and via Salesforce on the company's computer."		✓		✓	(Mallmann, Carlos, et al., 2018, p. 22)		✓	

Similarly, where formal system functionality does not meet user needs, an employee may transfer data to an informal system (Davison et al., 2019; Uppatumwichian et al., 2011). For example, when the formal system is inflexible for more complex analysis, an employee downloads the data (see this as transferring data) and analyses it in a spreadsheet (an informal system) (Davison et al., 2019). For example, where analysing data is a crucial requirement for an employee, the formal system design should offer the appropriate functionality (e.g., an interactive dashboard).

2.2.4.2 Store Data

Storing data is an activity where one puts data in an informal system. For example, users put the data on *cloud services* (Chua et al., 2014; Röder et al., 2015), *physical disks* (cf. Eikey et al., 2015; Silvius & Dols, 2012), *physical pieces of paper* (cf. Niazkhani et al., 2011; Saleem et al., 2009; Van de Weerd et al., 2019), or even a *database* (cf. Drum et al., 2017; Mallmann, Carlos, et al., 2018).

Storing data somewhere other than the formal system can create issues for an organisation. First, it allows a third party (e.g., a cloud provider – where the cloud service is used to store data) to create an opportunity to take *data* (Walterbusch et al., 2017).

Second, as time passes, this stored data will no longer belong to an organisation. The cloud provider can gradually replace data ownership (Walters, 2013). This situation may happen when the organisation does not continue their subscription to the cloud service. As such, there is no effort from the service provider to delete the data. Hence, *data ownership issues* can materialise.

Third, there is no guarantee that the cloud service is secure. Therefore, intrusions can happen at any time and create opportunities for *data breaches* to arise. Fourth, data stored off the formal system (e.g., cloud service) may, over time, lose its value. One reason is that the data format is no longer compatible with current applications (Walterbusch et al., 2017). So, storing data can produce *data compatibility* issues. Given these realities, storing data contains

"*inherent reputational damages*" for an organisation (Walterbusch et al., 2017, p. 654).

Research shows that employees store data in an informal system for several reasons. For example, employees make a *backup copy of the current system* to perform tasks more flexibly (cf. Mallmann, Carlos, et al., 2018). Also, employees make a backup because they perceive that the formal system is unreliable enough – it can fail at any time (cf. Khalil et al., 2017). For example, employees must be able to access the formal system anytime and anywhere. By doing so, the organisation can ensure the formal system's reliability.

Furthermore, research shows that ergonomic issues (e.g., navigation) can lead employees to store data elsewhere (Jagannath et al., 2018; Stevenson et al., 2018). For example, if a table in the EHR dashboard is too long, it can require horizontal/vertical scrolling. Hence, it is hard to find records when nurses do ward rounds (e.g., visiting patients). As a result, nurses store these data on physical paper (Jagannath et al., 2018; Stevenson et al., 2018). Over time, the nurse can enter data into the system later.

2.2.4.3 Retrieve Data

Retrieving data relates to gathering data from one or more data sources. For example, a medical provider fails to find necessary data stored in the EHR. As a result, they look for records elsewhere, such as asking colleagues, opening paper records, or utilising an old system (Bozan & Berger, 2018). The data source can be IT artefacts (cf. Drum et al., 2015; Fürstenau & Rothe, 2014; Spierings et al., 2017) or humans (Van de Weerd et al., 2019; cf. Wolf & Beverungen, 2019). As these data sources are typically fragmented, changes in data can be challenging to track. Hence, retrieving data can produce data issues for an organisation. For example, an employee can retrieve data from the wrong data sources (where the data are not current). As a result, data inaccuracies can materialise, producing misleading insights for managers.

Research shows that employees retrieve data from sources outside the formal system for multiple reasons. First, employees retrieve data because there is no accessible data in the formal system. For example, employees retrieve data because the necessary data are unavailable in the formal system (cf. Spierings

et al., 2017; Steinhueser et al., 2017). Also, they retrieve data elsewhere because they *perceive* that data are unavailable (cf. Huuskonen & Vakkari, 2013) or unavailable on time (cf. Walterbusch et al., 2017).

Second, along with data availability, employees retrieve data from other places because of data quality issues in the formal system. For example, *doubting* that the current *data* are *recent* (cf. Drum et al., 2016; Jagannath et al., 2019), *perceiving* that the *old system's data* are *reliable* (cf. Blijleven et al., 2019), or *formal system's data are too complex* to comprehend (Li et al., 2017). If there is an issue with data quality, employees must find data in other informal systems to resume their work.

2.2.4.4 Enter Data (Late)

Entering data late happens when one does not enter data promptly. Entering data late is prevalent in healthcare settings (cf. Safadi & Faraj, 2010; cf. Saleem et al., 2009, cf. 2011). Back-charting is a name for one of these practices (Jagannath et al., 2018, 2019). Back-charting is where a nurse writes patient data with a time stamp on a piece of paper and then enters the data into the EHR when they have spare time (Jagannath et al., 2018). Back-charting is a natural phenomenon in healthcare as nurses face busy daily workloads during medical dispensing (van den Hooff & Hafkamp, 2017). Back-charting may occur when a health professional's work ethos prioritises patient safety before data entry (Azad & King, 2012).

There are several issues with entering data late. First, as time passes, an employee can forget some vital information. Consequently, the inputted data can be *inaccurate* for future use by another data user (Stevenson et al., 2018). So, the data can become illogical (Thriemer et al., 2012). Second, forgetting important data can result in *data loss* (Thriemer et al., 2012). Third, as seen in healthcare settings, a nurse usually writes the data on paper first and then enters the data into the EHR at a later stage. So, double documentation occurs, which can lead to versioning issues (Stevenson et al., 2018).

Research shows that four factors contribute to entering data late. That is the *work ethos* of each individual (cf. Barrett, 2018; Ibrahim et al., 2019; Stevenson et al., 2018; van den Hooff & Hafkamp, 2017), *ergonomic issues* of

the formal system (cf. Ibrahim et al., 2019), *unreliable network infrastructure* (cf. Blijleven et al., 2019; Ibrahim et al., 2019), and *pre-processing of data* before entry (cf. Davison et al., 2019; Ibrahim et al., 2019; Jagannath et al., 2018; Li et al., 2017; Stevenson et al., 2018).

2.2.4.5 Enter Data (Inaccurate)

Entering data inaccurately happens when one does not input the correct data in the formal system. For example, an employee enters random codes for specific products (cf. Drum et al., 2017; Van de Weerd et al., 2019). This behaviour can result in inaccurate data (Drum et al., 2017; Li et al., 2017). Also, it leads to *data loss* (Beerepoot & van de Weerd, 2018). It can create insight distortion in downstream processes for downstream users (Drum et al., 2015, 2017) by creating uncertainty around actual transaction execution data.

Furthermore, research indicates that three factors can be responsible for this behaviour. That is, *work ethos* (Beerepoot & van de Weerd, 2018; Drum et al., 2015, 2017; Lovett et al., 2013; Reiz & Gewald, 2016; Van de Weerd et al., 2019; Yang et al., 2012), *poor policy* (Malaurent & Avison, 2016; Safadi & Faraj, 2010; Yang et al., 2012), and *inter-unit distrust* (Röder, Wiesche, & Schermann, 2014). These factors can influence behaviour as an independent or collective cause. Specifically, workarounds can result from inadequate organisational policies that reflect operational variabilities (Alter, 2014; Azad & King, 2012).

2.2.4.6 Analyse Data

Analysing data encompasses any activity to examine data for interpretation or explanation. This activity includes several data activities related to analysis. For example, they manually calculate data (Davison et al., 2019; Moss & Berner, 2015) or write *a report from available data* (Huuskonen & Vakkari, 2013; Van de Weerd et al., 2019). It is like an accounting employee examining the formal system's Accounts Receivable (AR) data. Here, the employee builds pivot tables on an informal system (e.g., a spreadsheet) and analyses them (Drum et al., 2016).

The impact of analysing data depends on the artefact used for analysis. For example, it is challenging to validate the accuracy of the analysis process when spreadsheets are used (Teo & Tan, 1997). Hence, analysing data can produce *inaccurate data*. Ensuring the document is the most recent is a challenge for paper-based analysis. In a similar vein, paper-based records tend to be fragmented. Hence, they can produce *incomplete* and *inaccurate data*.

Research suggests that analysing data occurs because the formal system fails to facilitate employees' analysis needs. So, each employee analyses the data outside the formal system – primarily spreadsheets (Blijleven et al., 2019; Davison et al., 2019; Drum et al., 2016; Ignatiadis & Nandhakumar, 2009). Research shows that the employee uses other "tools" for analysis. For example, employees ask other people (Flanagan et al., 2013; Röder et al., 2015; Röder, Wiesche, & Schermann, 2014) or (just) calculate the data on physical paper (Blijleven et al., 2019; Moss & Berner, 2015; Niazkhani et al., 2011).

The following section concludes the work. It examines the critical lessons learned. Also, it explains both the theoretical and managerial implications of the analysis. Finally, it outlines the limitations of the research and the opportunities for future research.

2.2.5 Conclusion

In doing a *theoretical review* (cf. Paré et al., 2015), this study uses an approach proposed by Webster and Watson (2002). This approach advises that literature review works *inductively* to produce a "*conceptual framework*" (Paré et al., 2015, p. 187; Webster & Watson, 2002, p. xiv). This study examines the coverage that WCDA has received in IS literature from 2009 to 2019. For this purpose, this study analyses 75 articles using open coding and presents a taxonomy of WCDA. It identifies three types of workarounds and discovers that these workarounds have 14 associated data activities.

2.2.5.1 Theoretical Contributions

This section discusses the theoretical implications of the work. It identifies three workaround types from empirical IS studies: *formal system use, informal system use, and human-proxy use.* In answering the second research

question, it highlights 14 data activities commonly associated with workarounds: *entering* (6 data activities), *transferring*, *storing*, *retrieving*, *analysing*, *comparing*, *manipulating*, *consolidating*, and *transforming data*. Also, it delivers an in-depth analysis of the six most frequently coded WCDA.

This study is keen to ensure that the theorising process is well documented. Karl Weick once said: "*theory cannot be improved until we improve the theorising process*" (Weick, 1989, p. 516). The methodology section walks through the step-by-step theorising process. So, it brings transparency to the approach for other researchers. Therefore, other researchers can evaluate the theorising process for *consistency* and *coherence* (Hammond, 2018). So, given these facts, the theorising process facilitates the emergence of theories that can well *describe*, *explain*, and *enhance* the understanding of an underexplored *phenomenon* such as WCDA.

Moreover, the proposed Taxonomy of WCDA serves as Theory Type I – Analysis (cf. Gregor, 2006). It identifies the data activities associated with workarounds (in an organisational setting) as a set of constructs where the nature of WCDA is *little known* (cf. Gregor, 2006, p. 624). Furthermore, this research has reached *concept saturation* (Webster & Watson, 2002). So, it believes that the taxonomy has satisfied the mandatory *generalisability of IS literature constructs, as Gregor (2006) suggested*.

Also, during open coding, this study ensures that each construct is mutually exclusive. Therefore, there is no overlapping definition. Thus, improving the constructs' *precision* (Mueller & Urbach, 2013), *accuracy* (Langley, 1999; Weick, 1989), and *clarity* (Gregor & Klein, 2014; Hassan & Willcocks, 2021). These features enable workaround researchers to build robust knowledge about WCDA.

2.2.5.2 Managerial Implications

The theoretical insights inform several implications for practice and trigger the call-out of some desired behaviours to manage WCDA and their impacts within the organisation. The first desired behaviour is *value-chain awareness*. This research theorises that each employee's value-chain awareness results from the WCDA consequences (either good or bad) (see Table 2.12). So, *value-chain awareness* (Porter, 1985) applies to all WCDA. If an employee has limited *value-chain awareness*, then the employee can execute mindless workaround-centric data activities. Employees may only care about completing their tasks without thinking of the data impacts caused downstream. As a result, there can be a bottleneck in the downstream process – because the data issues impede the execution of the process. They are subsequently producing implications for business performance.

As the desired behaviour, an organisation must develop *value-chain awareness* among its employees, across units, through several strategies. For example, the organisation can arrange regular business process workshops – that inform how data flows across functions/units. Employees must explain how the data they produce moves along the business process. The workshop must also identify what data issues an employee has experienced and where the issues originate.

The second desired behaviour is employees' *data discipline* (Iversen & Mathiassen, 2000). This desired behaviour is essential for entering data (see Table 2.12). An employee's *data discipline* facilitates entering good quality data "on time" into the formal systems. Otherwise, data timeliness becomes an organisational issue as the data are not there when needed (Jagannath et al., 2018). An employee's *data discipline* is closely related to their self-discipline. Thus, an organisation needs to set clear organisational goals around task completion, and employees must prioritise capturing data as part of task completion. An organisational culture that elevates the importance of capturing good quality data on the formal system in a timely fashion is critically important. It should be communicated frequently to all employees throughout the organisation.

Table 2.12 Desired Behaviours for WCDA.

No	Data Activity	Desired Behaviour			
		Value-Chain Awareness	Data Discipline	Working Knowledge and Skills	Operational Transparency
1	Transfer Data	✓			✓
2	Store Data	✓			✓
3	Retrieve Data	✓			✓
4	Enter Data - Late	✓	✓	✓	
5	Enter Data - Inaccurate	✓	✓	✓	
6	Analyse Data	✓		✓	

The third desired behaviour is *working knowledge and skills*. This study argues that employees need appropriate *working knowledge and skills* (Azad & King, 2012) (see Table 2.12). They must understand how the business process should materialise and how the organisational artefact can support it. For example, an employee must fully understand how the data should reflect actual transactions when entering data. Also, the employee must know where to enter the data into the formal system.

Without these understandings, the data quality in the formal systems can be impacted (e.g., inaccurate, incomplete, inconsistent) and produce misleading insights. Therefore, employees' *working knowledge and skills* can ensure that the data in the formal system can provide accurate, complete, and consistent insights when analysed. Some strategies can be introduced to develop *working knowledge and skills*.

Firstly, the organisation can arrange regular training for employees. This training can discuss techniques to enhance their work tasks. Secondly, the organisation can promote informal employee training (knowledge sharing) among employees. Thirdly, the organisation can incentivise employees to attend professional development courses and join professional networks. So, the organisation can improve its employees' working knowledge and skills by pursuing these strategies.

The fourth desired behaviour is *operational transparency* (see Table 2.12). This desired behaviour suggests that every data activity one employee completes should be transparent to other employees (Kosanke et al., 1999). For example, when an employee retrieves, transfers, and stores data, other employees must know these activities have occurred. Other employees must know where the data originated and where the data are now. This understanding is essential to avoid *issues with data loss*, *leak and privacy produced by such* activities (e.g., *retrieve data*, *transfer data*, and *store data*). To achieve *operational transparency*, the organisation needs to establish a collaborative culture. Each employee must be encouraged to share ideas with other employees. Also, the organisation needs to encourage open communication channels across organisational units. By doing so, the organisation can achieve necessary *operational transparency*.

Furthermore, as to relevance to practice, the research addresses three dimensions of relevance for practice (Benbasat & Zmud, 1999; Klein et al., 2006). These three dimensions are *importance*, *accessibility*, and *applicability*. As to its importance, this study shows that WCDA is a *real-world problem*. It gains *momentum* as more organisations are data-driven (Klein et al., 2006). Also, given the constructs, it designates that each potential *independent variable* is *practical* for managers. For example, managers can adjust these potential variables through direct actions, such as imposing policies (Robey & Markus, 1998).

This research avoids using complex research jargon in the theoretical insights to achieve greater clarity. Thus, it can reach broader audiences – e.g., academia and practitioners. It provides *advice and direction* for managers (Klein et al., 2006, p. 263). For example, the Taxonomy of WCDA provides

lists of data activities and their occurrences. Hence, the taxonomy helps identify and prioritise WCDA in organisations. It has demonstrated solid relevance *for management and policymaker decision-making* (Toffel, 2016).

2.2.5.3 Limitations and Future Research Directions

There are limitations to this study. First, it limits its search strategy to major IS databases. Other research from intersectional disciplines may produce different results. In this case, it attempts to reach saturation by examining as many articles as possible within the IS domain. So, other researchers from other disciplines can reach conclusions that may align with the theoretical outputs presented here.

Second, WCDA can be challenging to observe until the data impacts materialise. For example, consider an employee that *enters* data *incorrectly* (cf. Flanagan et al., 2013; Huuskonen & Vakkari, 2013) or *incompletely* (cf. Huuskonen & Vakkari, 2013). These WCDA impacts may not be identified until other employees use the entered data and feel the impact. However, these WCDA impacts cannot be uncovered if no employees use the data. Therefore, more empirical works are necessary to represent the true nature of WCDA. Researchers must capture longitudinal data (to see the impact of certain WCDA over time). Also, they must capture data from two perspectives (that of the data producer and the data consumer). As a result, this work can highlight the true impact of certain WCDA. It can reveal problems related to *entering data,* which are difficult to observe directly (e.g., entering inaccurate or incomplete data).

Third, as this study only analyses data from the literature, the Taxonomy of WCDA may not provide a complete picture of reality (for both data activities and their frequencies). Here, contextual matters for a particular organisation may facilitate the emergence of new overlooked data activity. Also, these contexts can determine the frequency of each data activity – which can differ from one organisation to another. They encompass various factors such as organisational domains, structures, processes, goals, time, and locations – where generalisation can be challenging. In this case, this research acknowledges that various organisational contexts can alter the Taxonomy of

WCDA. However, as this study analyses data from 11 years of workaround research (all articles are empirical), this study has covered most of WCDA.

There are potential future research opportunities. First, future research can investigate how WCDA artefacts (e.g., formal and informal systems) influence data quality. Research shows that artefacts can determine "*what information should be created, selected, and shared, with whom, in which format and in what sequence*" (D'Adderio, 2011, p. 216). Hence, they have a strong connection with data quality. However, the underlying mechanism that links certain WCDA artefacts and data quality is *unclear*. The mechanism must explain "how and why" certain situations and events develop over time. Subsequently affects data quality. This understanding raises the collective awareness of IS community actors of the existence of WCDA and WCDA artefacts as part of the analysis, design, implementation, and evaluation of enterprise-wide information systems.

Second, future research can examine the relationships among WCDA. The understanding of WCDA can support the construction of a complex and interdependent web of data activities. Various network analysis parameters such as centrality, density, and cluster can be helpful (Pentland, 1999). For example, centrality can help find the most "important" data activity across a web of data activities. Suppose a workaround can be seen as a process to accomplish work tasks. In that case, this "centralised" data activity is the bottleneck in the process. As a result, this data activity can stop the critical business process from progressing – not only the workaround. So, finding this data activity can improve the business process flow. In short, understanding centrality has a direct influence on business processes. It can help organisations size workaround risks from a risk management perspective. Therefore, it is beneficial to formulate more effective data governance programmes.

In the end, the article has addressed four questions, thus fulfilling the expectations of a comprehensive literature review (Webster & Watson, 2002): contribution ("what is new?"), impact ("so what?"), logic ("why so?"), and a thoroughness ("well done?"). This work has established a sound base for workaround researchers to build solid knowledge for continuing research around WCDA.

2.3 Conclusion

This chapter generates a taxonomy of Workaround-Centric Data Issues - WCDI (see Section 2.1) and Workaround-Centric Data Activities - WCDA (see Section 2.2) from IS literature. These taxonomies can be combined to produce a priori constructs.

There are several contributions to workaround research.

First, regarding WCDI, this study **challenges** the waterfall-style logic of the widely-cited Theory of Workarounds (Alter, 2014). It shows that WCDI can both *cause* workarounds and workarounds *create.* Hence workarounds can experience vicious cycles – if not well controlled. These vicious cycles can go unnoticed over time. Therefore, recognising this cyclical property can help researchers theorise *workaround evolution* and *impacts*. As such, it discourages having a simplistic perspective on workarounds, which assumes that workarounds are static and isolated to a particular unit. This perspective eventually calls for further observation and analysis to fully comprehend a workaround's intricate genealogy and related data activities and issues.

Second, regarding WCDA, this research **challenges** mainstream assumptions in workaround research, indicating that a workaround is *atomic* and *isolated* (Koppel et al., 2008; Vogelsmeier et al., 2008). It shows that a workaround can have a set of data activities as its integral components. So, a workaround is neither atomic nor isolated. As WCDA can be connected, this understanding facilitates future research in data-related *patterns of action*. Data-related impacts are closely related to these patterns of action. So, these patterns can help researchers understand workaround impacts more comprehensively. It can support us in overcoming existing challenges, thus creating new opportunities to improve the measurement of workarounds impacts.

Future research needs a reliable tool to analyse WCDA and their patterns of action. A Narrative Network is one such approach (Pentland & Feldman, 2007). The following chapter discusses a tool to visualise WCDA in organisations.

Chapter 3
Research Methodology

3.0 Introduction

This chapter explains how a modelling notation is developed to visualise WCDA in organisations (see Figure 3.1). This modelling notation includes a set of rules to visualise WCDA. It draws on the theory of organisational routines (Pentland & Feldman, 2007) to develop WCDA modelling rules. It is the first study to leverage the Narrative Network (NN) approach as a conceptual lens to model WCDA visually.

This study identifies five WCDA modelling rules: 1) a narrative fragment must come from a process actor; 2) a narrative fragment has three attributes: actor, action & resource; 3) all attributes in a narrative fragment establish the action type; 4) a narrative fragment must contain a data activity; and 5) a narrative fragment data activity must follow a standard naming convention.

These rules allow novice employees to visualise data-related activities in their working environment. They allow novice employees to visualise data-related activities in their working environment. Moreover, the narrative network facilitates further theorising in WCDA in organisations (see Table 3.1). It enables employees to relate one data activity and other data activities. By doing so, this research can show a web of action – where patterns of action exist.

Furthermore, this research demonstrates using a narrative network to model data activities within workarounds. It discusses the benefits and drawbacks of using this modelling approach. This study highlights using a narrative network for researchers to represent, observe, and analyse workaround-centric data activities.

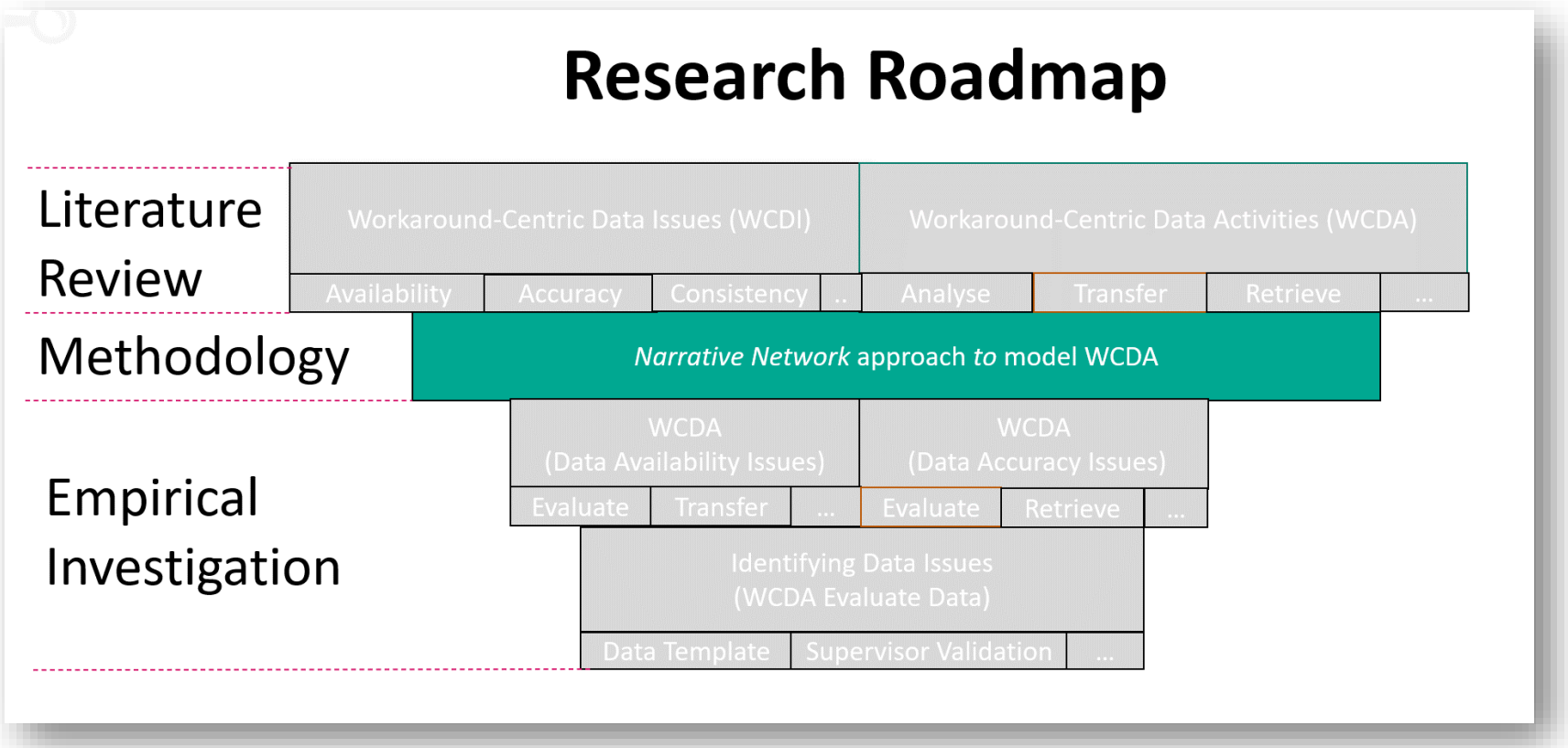

Figure 3.1 Research Roadmap: Research Methodology

Table 3.1 Extending Narrative Network - Planning Worksheet (Baird, 2021, p. 1207)

Item	Description	Details
Area of theoretical Focus	What theoretical area is being targeted?	This study develops *rules* to model workaround-centric data activities (WCDA) – by extending the Narrative Network approach (Pentland & Feldman, 2007). They produce Type V Theory (Gregor, 2006). It expects that this modelling tool can be helpful to theorise workaround-centric data activities.
Theoretical Backgrounds	What common ground is relevant to this area, your goal, and your target audience?	Common Ground: Workarounds impose data issues for organisations (Furstenau & Sandner, 2017; Khalil et al., 2017; Silic & Back, 2014). So, organisations must manage them carefully. One way to manage them is to model them visually (Röder et al., 2015). Research Objective: the research goal is to answer the following question: *What are the rules for modelling workaround-centric data activities (WCDA)?* Target Audience: Workaround researchers. Especially those who are interested in theorising workarounds.

Theoretical Tension	Why is a new theory needed?	The modelling rules produce Type V Theory (Gregor, 2006). These rules are a theory for design and action. They facilitate a methodology to theorise workarounds.
Resolution of theoretical tension	What is the primary aim of your theory paper?	This study aims to w*hat are the rules for modelling workaround-centric data activities (WCDA* by using the narrative network approach
	What theory-building (or extending) will the approach be applied?	This research extends the narrative network approach (Pentland & Feldman, 2007)
	What is the condition under which you develop your theory?	<u>Assumption(s):</u> This study assumes that the process modeller can isolate *"subject-verb-object"* from the interview. By doing so, the modeller can use this notation to model WCDA. It assumes that the employee is willing to share their experiences in doing workarounds.
Guidelines (For application)	What steps should future researchers go through when applying for this work?	Do some interviews and extract workarounds from them. One strategy is to isolate the *subject-verb-object* structure from interview texts. Here, each subject-verb-object structure acts as one narrative fragment. Later, a process modeller must link this narrative fragment with others. So, this study can articulate a complete workaround manifestation.

How can this work be extended?	This study can apply the approach in the real world and measure its applicability. For example, it can focus on highly-regulated organisations like healthcare, banking, insurance, pharmaceutical, finance, transportation, and manufacturing. Data are essential for these organisations to measure the alignment between process executions and regulation. Further, it seeks to understand what assumptions underpin WCDA modelling. These assumptions affect how employees produce the final NN. It later determines the plausibility of the NN. Fourth, it seeks to understand how the NN approach eases the emergence of tribalistic DG. For example, it intends to understand how tribalistic structures emerge from WCDA. Can it capture the most primitive DG functions that these structures have?

3.1 *Paper* 3: Plausible pictures for data governance: a narrative network approach

3.1.1 Introduction

Data Governance (DG) may be the most used - yet least understood term in today's business world. There is broad agreement on the *"importance"* and *"criticality"* of DG (cf. Berson & Dubov, 2011, p. 399). However, too many organisations are still *"undisciplined"* in their level of DG maturity (Fisher, 2009, p. 82). Research shows that DG initiatives cross *"functional, organisational, and system boundaries"* and are *"enormously challenging"* (cf. Berson & Dubov, 2011, p. 399). Nonetheless, they are considered strategically essential undertakings centred around *"mobilising organisational resources to leverage data as an enterprise asset"* (Berson & Dubov, 2011, p. 400). Therefore, at its most basic, DG is *"a methodology or a philosophy for gathering, managing, and benefiting from your data"* (Fisher, 2009, p. 65). In fact, according to Carruthers and Jackson (2018, p. 141), effective DG influences four data-specific areas (e.g., data *availability*, *usability, integrity*, and *security*). It can affect an organisation's regulatory compliance.

Research suggests that *"data are the lifeblood of an organisation"* (Fisher, 2009, p. 82). So, all transactional business data should be *"viewed through the lens of data quality"* (Fisher, 2009, p. 65). However, it is argued that most data quality (*integrity*) issues in organisations are linked to *"broken processes"*. Also, *"once the issues emerge, the search for scapegoats is on"* (Fisher, 2009, p. 83). The human agency linked to the execution of these "broken processes" motivates this study. This study focuses on the duality of structure and agency. Therefore, it replaces scapegoating with a visual understanding of the story behind the data activities to overcome data integrity issues.

In short, these data activities (linked to overcoming data integrity issues) are workaround-centric data activities (WCDA). For example, consider a situation where centralised system functionalities do not support an

employee's reporting need. As a result, the employee executes a workaround by *downloading* data from the centralised information system, *analysing* the data on a spreadsheet, and *uploading* the data back to the centralised information system.

In this case, *downloading*, *analysing*, and *uploading* data are examples of workaround-centric data activities (WCDA). So, these WCDA are efforts to improve DG maturity for an organisation - albeit they are most likely undocumented and poorly understood. As a result, this study needs to provide a means of creating plausible pictures for DG. By doing so, researchers can further advance the collective appreciation of such organisational innovations (these WCDA), especially in this era of digitally transforming and being data-driven.

Workarounds are not something those working in a centralised information systems environment want to hear when a business process is being described. The creativity that comes with workarounds often suggests that the organisation experiences system deficiencies. Therefore, such post-adoption behaviours can lead to significant organisational data challenges. So, while someone gets the job done, they may do so in a way that papers over the operational cracks (broken processes).

Over time these operational cracks can damage the organisational foundations and the value of its strategic data assets. After all, it has to be remembered that "*your data are your business*" (Fisher, 2009, p. 81) and "*it is a true competitive differentiator*" (Fisher, 2009, p. 82). However, bad habits around data create "*data debt*" (Carruthers & Jackson, 2018, p. 42). Therefore, this study argues that establishing *if WCDA are bad habits* should be a strategic priority in developing an initial theorisation of WCDA.

Even though workaround research has discussed WCDA – primarily as workaround examples, they are not the real focus of the investigation. Instead, researchers tend to describe WCDA as part of more general topics such as *compliance and data protection* (Burns et al., 2015; Eikey et al., 2015; Silic et al., 2017; Sillic, 2019; Walters, 2013), *adoption and resistance* (Alraddadi et al., 2018b; Behrens, 2009; Bozan & Berger, 2018; Malaurent & Avison, 2016; Zamani et al., 2013), *organisation misalignment* (Beerepoot & van de Weerd,

2018), *coordination* (Djalali et al., 2015), and *information quality* (Bozan & Berger, 2018; Drum et al., 2017). Therefore, even though WCDA have been studied, understanding of WCDA impacts on data remains incomplete.

One strategy to theorise WCDA is to model them as a chain of activities and analyse them. This strategy aligns well with previous research informing that a workaround constitutes a *set of activities* (Haag et al., 2015). So, researchers should not analyse a workaround as a single isolated action (Dunford & Perrigino, 2018). Researchers can use a modelling technique called a Narrative Network (NN) approach (Pentland & Feldman, 2007). Research shows that the NN approach benefits the model WCDA (cf. Wibisono et al., 2020). However, it does not have an existing ruleset as a guideline to model WCDA. Therefore, to support modelling WCDA, this study poses the following research question:

RQ. What are the rules for modelling workaround-centric data activities (WCDA)?

Developing these rules can help researchers uncover WCDA in their empirical studies, moving toward better WCDA theorisation. Also, modelling WCDA can enable organisations to create plausible pictures for DG. Creating plausible pictures for DG through visualising WCDA is akin to taking a *"bottom-up"* or organic approach to "*formalise informal data practices*" (Ladley, 2020).

This approach is pragmatic to getting started with DG meaningfully, especially where an organisation aspires to be data-driven. Redman (2016a, p. 2) highlighted that "*Most companies don't manage data very well"*. This situation presents a real challenge as most employees *"depend on data created elsewhere to do* [their] *work"*. Therefore, *"finding and fixing flawed data soon becomes a permanent fixture"* (Redman, 2016a, p. 1). While correcting errors in the data *"seems the fastest, most efficient way to complete the task at hand"*, it is, in fact *", expensive and time-consuming"* and *"doesn't work well"* (Redman, 2016a, p. 1). Therefore, to avoid finding and fixing flawed data, organisations need to *"prevent errors at their sources"* using *"data provocateurs"* (Redman, 2016a, p. 2).

A *data provocateur* is an individual who addresses data proactively, disrupts by advancing a data quality agenda, and challenges the status quo by questioning how they deal with data. As argued by Redman (2016a, p. 2): *"everyone whose job depends on data"* should *"see themselves as a potential provocateur"*. Therefore, this study uses the data provocateur role to highlight its target audiences. These target audiences can benefit from the approach presented.

The remaining sections of the research are as follows. Section 3.1.2 describes the theoretical background of the study. Next, Section 3.1.3 shows how this study extends the NN modelling approach and produces the rules for modelling WCDA. After that, Section 3.1.4 applies the proposed method in a hypothetical scenario (inspired by reality). It analyses and discusses the findings in Section 3.1.5. Finally, Section 3.1.6 concludes the results and highlights future research.

3.1.2 Theoretical Background

This section explains the theoretical background of the study. This study discusses the theory of organisational routines (Feldman & Pentland, 2003) and the three attributes of the NN approach (e.g., narrative, narrative fragment, and NN). It uses the theory of organisational routines (NN specifically) as a conceptual lens to represent and visualise WCDA. This theory can help understand how employees enact a process (e.g., a workaround).

3.1.2.1 Theory of Organisational Routines

It uses the theory of organisational routines because it underpins the original NN approach (Pentland & Feldman, 2007, p. 781). So, the theory facilitates sound ontological and epistemological stances. The theory of organisational routines is about *processes* that manifest in *organisations* – referred to as "organisational routines" (Feldman & Pentland, 2003; Pentland et al., 2012). Here, processes are "*repetitive*, *recognisable patterns of interdependent actions*, *which multiple actors carry out*" (Feldman & Pentland, 2003; Pentland et al., 2010; Pentland & Hærem, 2015). Organisational routines emphasise the duality of structure (e.g., *ostensive*) and agency (e.g.,

performative) (Feldman & Pentland, 2003). Research shows that duality is responsible for any change and stabilisation of a process (Feldman & Pentland, 2003). Thus, exploring these two aspects and their interactions is pivotal in understanding how a process evolves in an organisation.

The *ostensive aspect* is the ideal process form (Feldman & Pentland, 2003). It is a generalised idea regarding how a process should materialise (Feldman & Pentland, 2003, 2008). It is responsible for guiding an actor to execute a process in the future (Feldman & Pentland, 2003; Pentland & Feldman, 2005). The *performative aspect* is the actual performance. It manifests an *ostensive aspect* by *occurring with specific people, times*, and *places* (Feldman & Pentland, 2003).

An ostensive aspect can produce multiple performative aspects (Pentland & Feldman, 2005). For instance, consider a process of *order to cash* (OTC) by a wholesale company to sell goods to a customer. Typically, the process encompasses four consecutive activities: sales order, goods shipment, invoicing, and payment. However, situations can vary in the real world. For example, a customer can make the payment (down payment) and later accept goods shipments. However, a customer may obtain the invoice first before receiving the goods on another occasion. Also, the payment may never occur if a customer refuses to pay. In this case, one can see how an ideal form can turn into multiple performances. Hence, a single observation "is insufficient" to capture the performative aspect of a process. If some of these performances do not have or do not follow a script, then they are viewed as workarounds.

3.1.2.2 Data Activities and Workarounds

This study defines a workaround as an adaptive process in a centralised system environment. All actions are assumed to be mindful and purposeful as an adaptive process. So, mindless actions (e.g., inattention, accidents, or mistakes) are not workarounds - even though, eventually, they may produce unexpected events or changes. As an adaptive process, it views workarounds as follows:

1. A workaround is a process that does *not have* a formal script.
2. A workaround is a process that does *not follow* a formal script.

A workaround is a purposeful adaptation to overcome workflow disruptions in a centralised system environment. As a process, a workaround can contain one or more data activities. A data activity is an activity that relates to organisational data—for example, consuming, producing, manipulating, storing, and transferring data. A non-data activity encompasses any action that does not involve organisational data. For example, a nurse measures the patient's vital signs, records them on a paper-based file, and inputs them into the hospital information system. This study has two data activities (e.g., record and input) and one non-data activity (e.g., measure).

Table 3.2 The typology of action

Action	Workaround	Non-Workaround
Data activity	Type 1	Type 2
Non-data activity	Type 3	Type 4

A data activity can be performed in both workaround and non-workaround actions (see Table 3.2 – Type 1 & Type 2). For example, if nurses enter data on the Electronic Health Record (EHR) *late* or *incompletely*. Similarly, they do so in a way that does not follow the SOP (standard operating procedure) for the specific process in question. Therefore, this *pattern of action* can be the WCDA (workaround-centric data activity) characteristic.

3.1.2.3 Narrative, Narrative fragment, Narrative network

The NN approach embodies three components: narrative, narrative fragment, and narrative network (Pentland & Feldman, 2007). A narrative is a sequence of events with a specific goal, with each event having a clear *start*, *middle*, and *end*point (Pentland & Feldman, 2007). For example, consider the "plan a holiday" story. One can enter the travel website (*start*), book a hotel (*middle*), book a flight (*middle*), and pay the bill (*end*). A narrative must have moving actions (from *start* to *end*) to be valid (Feldman & Almquist, 2012). Also, the order of these actions must be *meaningful* for achieving the stipulated

goal (Feldman & Almquist, 2012). If one randomly re-arranges the order of the actions, then the narrative can be questionable. That is, pay the bill (*start*), book a hotel (*middle*), enter the travelling website (*middle*), and book a flight (*end*). Here, the sequence is illogical (e.g., how can one pay *without* entering a website and booking something?). Hence, the order should be logical to create a plausible narrative.

The second component is the narrative fragment – which later becomes the atomic building block for the NN (Pentland & Feldman, 2007). It comprises at least two *actants* (either human or nonhuman) and one *action* that links them (Pentland & Feldman, 2007). For example, "the *user* visits the *website*", "the *web server* authenticates the *user*", and "the *firewall* blocks the *protocol*" (Pentland & Feldman, 2007). For these examples, an employee has five actants (e.g., user, website, web server, firewall, protocol) and three actions (e.g., visits, authenticates, blocks). Furthermore, Pentland and Feldman (2007) expect that the action within a narrative fragment has a timespan. This timespan expresses that the actant requires *time* to complete a task. This timespan also means a legitimate action should have determined start- and end-points (*not infinite*).

The third concept is the NN. A NN is a directed dyadic graph expressing interconnected narrative fragments chronologically (Pentland et al., 2017; Pentland & Feldman, 2007). It signifies the coherence of the narrative fragments in a unity of purpose (Pentland & Feldman, 2007). Moreover, a NN represents one process (Pentland & Feldman, 2007). Hence it is a process model (Hayes et al., 2011; Yeow & Faraj, 2011). According to the theory of organisational routines, a single actor only understands parts of the process (*not complete*) (Feldman & Pentland, 2003; Pentland, 1999; Pentland & Hærem, 2015). Therefore, the NN approach must involve multiple actors to construct the process.

For this reason, a NN must accommodate multiple narratives in one graph – even though some narratives vary significantly from others (Pentland & Feldman, 2007). A NN signifies and visualises patterns of action (Pentland et al., 2017; Pentland & Feldman, 2008, p. 244). It articulates actual and potential patterns (Pentland & Feldman, 2008). Consequently, it can capture the complex inter-relationships across actors' viewpoints on completing tasks

(Hayes et al., 2011). These features are pivotal to model WCDA. The following section explains the proposed approach and the WCDA modelling rules. Furthermore, this study focuses only on Type 1 and Type 2 activities (e.g., data) to achieve the research objectives.

3.1.3 Proposed Research Approach

This section explains the WCDA modelling rules. After that, it considers a hypothetical scenario (inspired by reality) and uses these modelling rules. It builds a plausible picture for DG by modelling WCDA visually.

3.1.3.1 Constructing a Narrative Network

The proposed approach is based on *four general steps to construct a NN* (Pentland & Feldman, 2007). These four steps are relevant and helpful. Nevertheless, they are generic. So, researchers need to elaborate on the idiosyncrasies of WCDA. For this reason, this study extends the steps by proposing the five modelling rules uniquely for WCDA modelling. Therefore, when using the four steps to construct a NN, it applies Rule 1 to Step #2 and Rules 2, 3, 4, and 5 to Step #3 (see Table 3.3). These five rules within the four steps are now presented below.

Table 3.3 Rules to construct a narrative network.

No	Step	Note
1	Choose a process and define its boundary	Focus on the "purpose."
2	Adopt a point of view	*Rule 1*
3	Collect the narratives and code the fragment	*Rule 2, Rule 3, Rule 4, Rule 5*
4	Relate code with sequences	Visualise the NN

3.1.3.2 Step #1. Choose a process and define its boundary.

For step #1, a data provocateur must select a process to examine (cf. Pentland & Feldman, 2007). An organisational process can be part of an infinite web of actions. Thus, it can have an unclear boundary (e.g., where to start and

end). A data provocateur must articulate a process based on its purpose to solve this issue. Thus, it can have a more explicit boundary. For example, consider a *training personnel* process. The process can be part of both a "regular training process" and a "vendor billing process" (see that the process has two purposes for training personnel).

Each process can involve actors from two or more different units. So, as a combination of perspectives, the process can become very complex. In this situation, the data provocateur must select one purpose, ignoring the others. The data provocateur can determine the start and where the process should end with an explicit purpose. This information is essential to determine the actors in the process. A data provocateur can extract their point of view (see step 2).

3.1.3.3 Step #2. Adopt a point of view.

Step #2 outlines that the data provocateur needs to collect narratives to build a NN (cf. Pentland & Feldman, 2007). The data provocateur and other stakeholders must understand how the process works (Pentland & Feldman, 2007). For example, consider the process of *regular training* where trainers, supervisors, and managers can know how employees execute the process. As their stories tend to be fragmented, they must select the most appropriate point of view to represent the actual enactment of the process.

This study needs to know where the workaround actors reside to address the research objective. So, to answer this question, this study develops *Rule 1* from the theory of organisational routines. This theory informs that a process contains *ostensive* and *performative* aspects. The ostensive aspect indicates the abstract idea about how an actor performs a routine. The performative aspect shows the actual performances of the routine (Pentland & Feldman, 2005).

Moreover, the theory informs that the performative aspect is highly associated with specific actors (e.g., process actors) (Feldman & Pentland, 2003; Pentland & Feldman, 2008). Here, a process actor is the one who executes one or more activities. Process actors typically work at an operational level (e.g., operator, administrator, clerk). These process actors can take improvisational actions to overcome "broken processes" situations.

Further, process designers, owners, managers, and supervisors are not "process actors" unless they directly enact a process. Since process actors are the actual process enactors who can take improvisational actions, they can be considered workaround actors. Therefore, one way to capture workarounds is to identify all process actors and then narrate the workaround story from the perspective of these actors. Hence, process actors are the best sources to establish narrative fragments.

Rule 1. A narrative fragment must come from a process actor.

3.1.3.4 Step #3. Collect the narratives and code the fragment.

Step #3 outlines that the data provocateur needs to collect narratives from process actors and code the narrative fragments accordingly. A *narrative fragment* is the building block of the NN approach and consists of at least two actants and one action (Pentland & Feldman, 2007). Following the actor-network theory, an actant can be both human and nonhuman (Pentland & Feldman, 2007). So, given the research objective to model WCDA, this study uses three attributes to construct each narrative fragment for the second rule. These attributes are *actor*, *action,* and *resource.* Here, actor and resource are both extensions of actant. An *actor* is someone that *acts*. In the context, the actor MUST be a *human* because "technology appropriation" (e.g., workarounds) is only viable whenever the process actor is *human*. Action is the activity that an actor performs (Pentland et al., 2012). In this case, it must reflect the data activity. For example, *analysing* data, *transferring* data, and *storing* data.

Further, every action requires a resource the actor uses to execute. There are three types of resources: *human*, *artefact*, and *data*. A resource can be a *human* (e.g., an "intermediate actor") that an actor uses to complete the action, in other words: a proxy. For example, a physician uses a medical scribe to record data when interacting with patients during consultations (Barrett, 2018). An *artefact* is a human-made object with specific objectives (D'Adderio, 2011). Here, it is part of a process and assists an actor in executing an action. It has technical functions—cloud services, paper-based files, software, and USB

sticks. Finally, *data are* any symbol or representation of specific events. Data must be attached to an artefact or a human during process execution.

Rule 2. A narrative fragment has three attributes: actor, action & resource.

For the third rule, a narrative fragment is a composite component (consists of three attributes: *actor*, *action* & *resource*). It exists at the atomic level (Pentland & Feldman, 2007). Therefore, this study cannot use a single attribute (e.g., *action*) to establish if the narrative fragment represents a workaround. Also, it must examine the *actor* or the *resource* associated with the *action*. For example, physicians use their own devices (*unauthorised resources)* to store data (*action*) from the EHR. Another example is a physician using a medical scribe (*unauthorised actor*) to enter data (*action*) in the EHR or a physician entering data (e.g., a patient's diagnosis) in the wrong EHR field (e.g., text area instead of using a drop-down menu) (an *action* incorrectly using *a resource*). Therefore, it must assess the three attributes in combination to determine the *nature* of an *action* to establish if it is a workaround.

Rule 3. All attributes in a narrative fragment establish the action type.

For the fourth rule, the theory of organisational routines informs that all narratives should be coherent. For example, narratives ensure that the sequence of events demonstrates the similarities of purpose or goal (Feldman & Pentland, 2008; Pentland & Feldman, 2007). Therefore, this study only aims to visualise the data aspect after identifying the narratives. Therefore, a data provocateur needs to model the data activities only (Action Types 1 & 2) and exclude the non-data activities (Action Types 3 & 4). By removing non-data activities, the data provocateur can simplify the NN.

Rule 4. A narrative fragment must contain a data activity.

For the fifth rule, the theory of organisational routines informs researchers that understanding a routine can vary from one person to another (Pentland & Feldman, 2005). As a result, two actors can label an identical action with two different names. For example, sending data (cf. Ignatiadis &

Nandhakumar, 2009), transferring data (cf. Zimmermann et al., 2016), and transmitting data (cf. Chua et al., 2014) can refer to the same data activity. So, as a routine grows into a complex web of action (Pentland & Hærem, 2015), labelling identical actions with inconsistent naming conventions can create issues. Therefore, this study must standardise the label for such a data activity.

Rule 5. A narrative fragment data activity must follow a standard naming convention.

3.1.3.5 Step #4. Relate code with sequences.

After coding all narratives into narrative fragments, this research relates them into an ordered chain (Pentland & Feldman, 2007). A data provocateur needs to determine the order of the fragments. The output from this step is a complete NN to visualise the data activities (both workaround and non-workaround). The following section demonstrates the WCDA modelling approach.

3.1.4 Applying the Approach in a Hypothetical Scenario

This section explains how this study transforms a narrative into a narrative fragment and further into a NN. To achieve this goal, it devises a hypothetical scenario inspired by reality. It uses this scenario to achieve practical clarity in applying the method in a data-centric scenario. This scenario shows how to transform the narrative into narrative fragments containing Type 1 and Type 2 actions only (e.g., data activities). This scenario differs from the traditional NN approach, requiring articulating all activities (e.g., Types 3 and 4). After that, this section presents a brief analysis of the NN.

3.1.4.1 The Hypothetical Scenario Inspired by Reality

This study develops a hypothetical scenario describing one patient's hospital admission (see Table 3.4). Following step #1 (see Table 3.4), the *purpose* of the process is to admit a patient to the hospital and assess, diagnose, and treat them (see Table 3.4).

Table 3.4 A hypothetical scenario (inspired by reality)

A 40-year-old female presents with flu-like symptoms at the Emergency Department (ED). An ED administrator captures biographical data and symptoms to create an ED patient chart. Later, the triage nurse captures temperature, blood pressure, and blood oxygen readings. Next, she records them on the ED patient chart. She also checks other biographical data with the patient (e.g., date of birth, gender) and mobile number, health insurance policy number and a history of the symptoms. *At this point, the triage nurse instructs the patient to go to an ED examination suite for examination by an ED consultant. Sometime later, the ED consultant examines the patient. The consultant corrects the symptoms on the patient chart based on the patient's responses. However, the result contradicts the earlier account provided to the triage nurse and the admissions officer. The ED consultant suggests administering medication to reduce the patient's temperature. Before leaving the examination suite, the consultant suggests that a member of their ED team arrives with the medication shortly. The consultant leaves and takes the patient chart with them in error. Some minutes later, another ED physician brings the medication for the patient. They do not have the patient chart to hand. So, they record the dose and time on their dispensing chart and post-it notes, which they stuck to the end of the patient's examination suite bed.* *Because the ED is busy, the physician sends the medication dose and time to the ED consultant over WhatsApp. The ED physician explains that because the ED consultant has the patient chart. Therefore, they can record the medication dose and time data later. They take it from the post-it (if in the room) or the WhatsApp message if elsewhere. Roughly 30 minutes after taking the medication, the patient's temperature is not normalising. Later, the ED consultant visits the patient. The ED consultant asks the patient how they feel, if they recall the medication, and when. The patient confirms how they feel.* *Also, the patient refers to the post-it note (at the end of their bed). Besides, the physician administering the medication sends a WhatsApp message to the consultant to create a digital record of the dose and time. The consultant takes the post-it and records the dose and time on the patient chart. However, in doing so, the ED consultant also checks the WhatsApp message to ensure the details are correct. The ED consultant suggests that the patient be admitted to the hospital for overnight observation. The consultant informs the patient that their hospital admission patient record can be completed once they are settled in the hospital ward. About one hour later, the patient is transferred to the hospital ward. The ward nurse updates their digital admission patient record. The ward nurse also refers to the ED patient chart and clarifies some information directly with the patient. The ward nurse took a swab from the patient and sent it to the lab to test for the flu.*

Further, the scenario is presented as a narrative. So, the reader of this research (a prospective *data provocateur*) can identify the narrative fragments (*actor*, *action,* and *resource*) and code the Type 1 and Type 2 actions only. Also, the scenario is assumed to represent a complete extract of an operative's (e.g., process actor's) narrative.

From the narrative in Table 3.4, this study extracts actors, actions, and resources based on the *subject-verb-object* structure to build the narrative fragments (Pentland & Feldman, 2007). A subject is represented as an actor, a verb as an action, and an object as a resource. For example, in the sentence "an ED administrator captured biographical data and symptoms to create an ED patient chart", the subject (actor) = ED Administrator, the verb (action) = Captured data, and the object (resource) = [i] Biographical Data and Symptoms (data resource) and [ii] ED Patient Chart (artefact resource) (see NF2 in Table 3.5) For this coded translation). This scenario comprises six actors: an ED administrator, triage nurse, ED consultant, ED physician, and Ward Nurse (see Table 3.5). Once all the narrative fragments are extracted from the scenario (Type 1 and Type 2 actions only). Further, it standardises the name of each narrative fragment's action to improve the readability of the resulting NN.

3.1.4.2 Unpacking the Hypothetical Scenario

Figure 3.2 shows the final visualisation, a NN containing all narrative fragments in sequence. Four of the 16 data activities are Type 2 (non-workaround). These activities are *retrieve*, *enter*, *transfer*, and *store* data (see Figure 3.2). Within the NN, both *retrieve* and *enter* data are the most frequent data activities, followed by *compare* data. Furthermore, this study shows that a completed data activity can become a WCDA when another actor uses the data. For example, consider NF_1, where an ED actor enters data in the formal system. This action is a regular activity. However, when another ED actor reads the data, they find it incorrect (e.g., NF5) and correct them.

Table 3.5 Narrative fragments extracted from the scenario.

NF	Action Type	Actor	Action	Resource		
				Human	Artefact	Data
1	Type 2	ED Administrator	Capture data (retrieve data)	Patient		Biographical data and symptoms
2	Type 2	ED Administrator	Create data (enter data)	-	ED Patient chart	Biographical data and symptoms
3	Type 2	Triage Nurse	Measure vital signs (retrieve data)	-	Medical Devices	Temperature, blood pressure and blood oxygen
4	Type 2	Triage Nurse	Enter vital signs (enter data)	-	ED Patient chart	Temperature, blood pressure and blood oxygen
5	Type 1	Triage Nurse	Check data (compare data)	Patient	ED Patient chart	Date of birth, gender, mobile number, health insurance policy number, history of the symptoms
6	Type 2	ED Consultant	Examine (retrieve data)	Patient	-	Patient's examination data
7	Type 2	ED Consultant	Correct data (enter data)	-	ED Patient chart	Patient's examination data
8	Type 1	ED Physician	Record data (store data)	-	Dispensing chart	Medication dose and time
9	Type 1	ED Physician	Record data (store data)	-	Post-it Note	Medication dose and time

10	Type 1	ED Physician	Send data (transfer data)	-	WhatsApp	Medication dose and time
11	Type 1	ED Consultant	Ask for data (retrieve data)	Patient	-	Medication dose and time
12	Type 1	ED Consultant	Ask for data (retrieve data)	-	Post-it Note	Medication dose and time
13	Type 1	ED Consultant	Record data (enter data)	-	ED Patient chart	Medication dose and time
14	Type 1	ED Consultant	Check data (compare data)	-	WhatsApp, ED Patient chart	Medication dose and time
15	Type 1	Ward Nurse	Update data (Enter data)	-	Digital Patient Admission Record	Patient's record
16	Type 1	Ward Nurse	Clarify data (compare data)	Patient	ED Patient chart	Patient's record

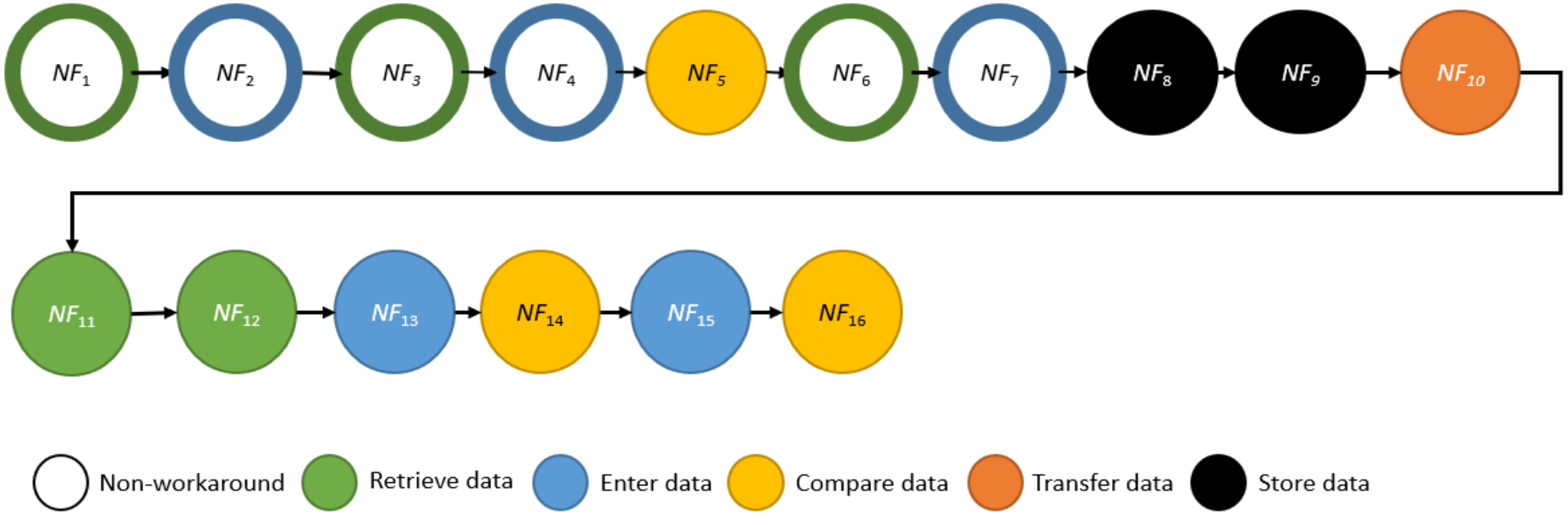

Figure 3.2 The scenario NN

Therefore, data provocateurs must identify a pattern of action in their narrative. Once they find it, they must reclassify the previous data activity (e.g., NF_1) as a workaround (WCDA). A data provocateur can observe at least two patterns of action from the codified hypothetical scenario.

First, a pattern of *enter data* precedes *compare data* on three occasions (see $NF_4 – NF_5$; NF_{13} - NF_{14}; NF_{15} - NF_{16}). This *pattern of action* indicates that workarounds occur *retrospectively* and not *prospectively*. For example, actors execute the action first (e.g., *enter data*) and check whether the data are correct later (e.g., *compare data*). Correcting data is retrospective because actors look back on something in the past. This situation is different from that advised by (Alter, 2014). He that workarounds are *prospective*, in that an actor develops a set of alternatives before executing a workaround. Given this observation, the NN approach can facilitate further workaround theorising.

Second, a data provocateur can observe that actors *store data* twice (see $NF_8 – NF_9$). This pattern of action can be an indicator that *data duplication* is occurring. As a result, the ED department (as in this scenario) can experience *data inaccuracy* as data duplication requires actors to reconcile data if/when differences arise in future use. Further, data loss can also occur because the reconciliation process can unintentionally remove facts. Therefore, the data provocateur needs to provide relevant measures to avoid this pattern of data duplication, which reveals the value of the NN as a plausible picture for DG.

Third, the data provocateur can observe that a workaround can create another workaround. For example, an actor can enter data *incompletely* (see NF_{13}). As a result, other actors must re-enter the missing data (see NF_{15}) and clarify the data (see NF_{16}). Here, one can see that both NF_{15} and NF_{16} are workarounds that materialise to compensate for the previously enacted workaround (NF_{13}).

3.1.5 Discussion: Plausible Pictures for Data Governance

WCDA can be hard to identify. As stated earlier, while these WCDA are often innovative efforts to improve organisational DG maturity, they are most likely undocumented and somewhat invisible. Therefore, the proposed approach for creating plausible pictures for DG emphasises plausibility over

accuracy in providing such visibility. This section elaborates on the advantages and disadvantages of the approach.

Modelling WCDA provides some benefits. First, it reveals how a process materialises and explains how the process's data are created, analysed, and used. Second, the relationships among narrative fragments can reveal the most critical actors in a process. Third, it exposes what artefacts are frequently used to store or process data. By having this information, a data provocateur can better understand the realities of the process landscape. By doing so, the data provocateur can formulate better data-related policies.

Moreover, a NN approach has advantages in modelling WCDA visually. First, it helps data provocateurs accommodate diverse viewpoints, i.e., how different actors execute a process (Pentland & Feldman, 2007). This feature helps deal with the unique and situational characteristics of workarounds. Once these characteristics surface, two actors can have different viewpoints about how a workaround materialises (D'Adderio, 2011; Feldman & Pentland, 2003). Second, a NN approach establishes a shared vocabulary for multi-level organisational stakeholders (Pentland et al., 2017). A NN contains sequential relations among actions in chronological order to follow the flow (Pentland et al., 2017). Therefore, all organisational stakeholders can examine the different patterns of action and share their interpretations with others (Pentland et al., 2017). This step is pivotal to ensuring that the NN is unbiased, complete, and capable of improving its accuracy.

However, the proposed NN approach has limitations. First, research indicates that WCDA can materialise as "no action" (do nothing). For instance, a physician does not enter data in an EHR (Blijleven et al., 2019; van den Hooff & Hafkamp, 2017). Thus, subsequent users' critical data are missing (Jagannath et al., 2018, 2019). Second, a workaround can be naturally *unobservable* (Wibisono et al., 2020). For instance, *entering data* can be a workaround – even though it looks like a regular activity. Sometimes an employee can enter data *inaccurately.* Otherwise, they enter the data *incompletely* or *in the wrong location*. To unearth such *unobservable* situations, a data provocateur must try hard and probe to model all data

3.1.6 Conclusion

To achieve a certain level of quality, data provocateurs must establish how employees create, analyse, and use operational data. Data provocateurs need to visualise how a business process is enacted. They must show how the data are produced and consumed throughout the business process and by whom. So, this study proposes extending the NN approach (Wibisono et al., 2020) to model WCDA. Following this strategy, drawing from the theory of organisational routines (Feldman & Pentland, 2003), it proposes five WCDA modelling rules. These rules are helpful for data provocateurs to assure meaningful and quality outputs for DG. Further, it leverages the approach to model WCDA using a hypothetical scenario. So, it can represent, observe, and analyse workarounds and their data activities, thereby understanding the true nature of the data activities associated with business processes.

3.1.6.1 Theoretical and Practical Contributions

In terms of theoretical contribution, this study advances the applicability of the NN approach by providing rules to model and visualise WCDA. These rules serve as the novelty of the work. These rules complement the generic guidelines for using the NN approach proposed by Hayes et al. (2011), Yeow and Faraj (2011), and Feldman and Almquist (2012). However, these general guidelines have limitations. First, they assume that the process is predetermined and standard. WCDA are NOT predetermined and standard. Second, they exclude data as essential elements in the narrative network. Third, they do not standardise the label used in the NN approach. So, modelling WCDA can be challenging. It shows how to visualise workarounds and their data activities.

There are some advantages to using the proposed NN approach. First, it is a user-centric approach. It does not require elaborate technical process mapping expertise. Second, it can compile multiple viewpoints in a single diagram (Yeow and Faraj, 2011), visualising resource and actor variabilities. So, it democratises modelling efforts in an organisation.

Furthermore, the research community can use the approach as a theory-building tool. For example, narratives gathered for a specific process can be

analysed quickly (leveraging standardised data activity names) to highlight the patterns of action associated with the workaround. These benefits can lead to a complete understanding of WCDA. Hence, this study contributes to the workaround literature.

As to practical contributions, previous research shows that workarounds tend to be hidden and are challenging to find (Mallmann, Carlos, et al., 2018; Silic & Back, 2014). The five modelling rules can facilitate data provocateurs to find and visualise WCDA. As a result, data provocateurs can produce a quality process model, which is indispensable for formulating relevant data-related policies. These policies are essential to ensure that an organisation can maintain data quality/integrity over time. Also, these rules can serve as guidelines to support collaboration among data provocateurs. These data provocateurs can better allocate individuals to capture business processes based on the rules. Similarly, it helps to reconcile differences across process models (e.g., by standardised naming of data activities).

3.1.6.2 Implications

These implications target organisation employees, particularly data provocateurs responsible for day-to-day data provision. As organisations are now primarily data-driven, data pervasiveness and complexities are evident. Data issues severely impact all organisational levels – from operational to strategic (Khatri & Brown, 2010).

Where the NN approach is user-centric, it facilitates a new approach to DG. It allows domain experts to reflect on how they produce, consume, and transfer data. So, the NN approach provides an accessible, flexible, and innovative approach to revealing insights about data activities. Organisations can leverage these insights to inform ongoing or future DG programmes/strategies.

Further, this new DG approach is not a top-down approach, as is often the case with regular DG initiatives. Instead, it is a novel bottom-up approach. Therefore, it has the potential to respond and react to changes to data activities occurring "on the ground". Employees who work on the same "working goals" belong to the same *data tribe.* They can eventually visualise and govern their

data with minimal intervention from top management. Therefore, this study calls this concept *tribalistic data governance*.

A tribalistic DG structure can emerge by isolating actor-relationships in the generated *patterns of action*. The structure reflects how these actors (e.g., employees) work, capturing nuances of work beyond formal organisational structures. Therefore, it can better reflect data-related roles and responsibilities. This strategy addresses one DG challenge: data flow and logic may not follow the formal structure of an organisation (Janssen et al., 2020). Also, the organisation can establish DG functions based on this structure. These functions refer to master activities for effective DG, such as policies, principles, processes, and decision rights (Al-Ruithe et al., 2019). So, the organisation can introduce relevant and applicable DG functions over time. With these functions, organisations can solve several barriers to deploying DG: lack of policies, processes and defined roles (Al-Ruithe et al., 2016). By doing so, organisations can avoid and mitigate data silos in organisations. Also, organisations can improve organisational DG maturity.

3.1.6.3 Future Research

This study outlines several research opportunities. First, researchers can use the approach in the real world and measure its applicability. For example, researchers can focus on highly-regulated organisations like healthcare, banking, insurance, pharmaceutical, finance, transportation, and manufacturing. Data are essential for these organisations to measure the alignment between process executions and regulation.

Second, it can compare the NN approach to industry-standard modelling approaches such as Business Process Modelling Notation (BPMN). This comparison can further interrogate the NN approach's strengths and weaknesses, particularly as an accessible and flexible means of visualising WCDA.

Third, future work can investigate how employees develop their modelling rules for WCDA. Primarily, researchers can seek to understand what assumptions underpin WCDA modelling. These assumptions can affect how

employees produce the final NN. It subsequently determines the plausibility of the NN.

Fourth, this study strives to understand how the NN approach facilitates the emergence of tribalistic DG. For example, researchers intend to comprehend how tribalistic structures emerge from WCDA. Can future studies capture the most primitive DG functions that these structures have? What are they? How are these structures related to each other? Given these structures, who is responsible for overseeing them? Hence, it can introduce effective alternative strategies to govern data. By doing so, organisational DG maturity can be further enhanced.

3.2 Conclusion

This chapter describes how to develop a modelling notation for visualizing WCDA. This modelling notation contains a set of rules for visualising WCDA. This study utilises the theory of organisational routine (Pentland & Feldman, 2007) to develop WCDA modelling rules. It is the first work to use the Narrative Network (NN) approach as a conceptual lens for visually modelling WCDA.

There are five WCDA modelling rules: 1) a narrative fragment must come from a process actor; 2) a narrative fragment has three attributes: actor, action & resource; 3) all attributes in a narrative fragment establish the action type; 4) a narrative fragment must contain a data activity; and 5) a narrative fragment data activity must follow a standard naming convention.

This study shows how to use narrative networks to model data activity within a workaround. This modelling notation and rules can help researchers map, observe, and analyse WCDA.

The next chapter applies these modelling rules to field studies. It investigates WCDA and their patterns of action in five field studies in Indonesia. By modelling these patterns of action, this study elucidates how specific data issues (e.g., availability and accuracy) influence data employee behaviours as *curative* practices.

Chapter 4
Empirical Investigation

4.0 Introduction

This chapter aims to understand how interconnected WCDA manifests as patterns of action in dealing with data availability and accuracy issues (see Table 4.1). So, it discusses the empirical works of this research project. The literature review informs that data availability and accuracy are organisations' most frequent data issues (see Figure 4.1). Hence, data availability and accuracy issues merit further investigation.

Section 4.1 focuses on data availability issues. A field study of a Quality Assurance (QA) unit of an Indonesian sugar plantation company is presented to unpack these often-invisible WCDA patterns of action. Open coding and a narrative network (NN) approach are used to complete the analysis. The findings reveal that data availability issues produce three patterns of action: dual inspection, prudent control, and mindful handling.

Section 4.2 focuses on data accuracy issues. It conducts three field studies in Indonesia: a plantation company, a government agency, and a university. This research uses open coding and the narrative network approach to present emerging patterns as part of the analysis. So, it finds that organisations execute three patterns: field inspection, fast authorisation, and gold standard making. Also, it explains how the Javanese values of *kekeluargaan* inform these patterns.

Furthermore, *evaluate data acts as* the common dominator across all data activities. This activity is observable in all identified patterns as it always materialises. Therefore, this study examines how employees find data issues as a sub-process within *evaluate data* (see Figure 4.1). For this purpose, Section 4.3 investigates how employees identify these data issues in five field studies. Organisations can execute five "checking" approaches: *data template, supervisor validation, data accuracy, consistency, and data completeness*. This research discusses each approach, theorises its interrelatedness, and explains its contributions to data quality research and practice.

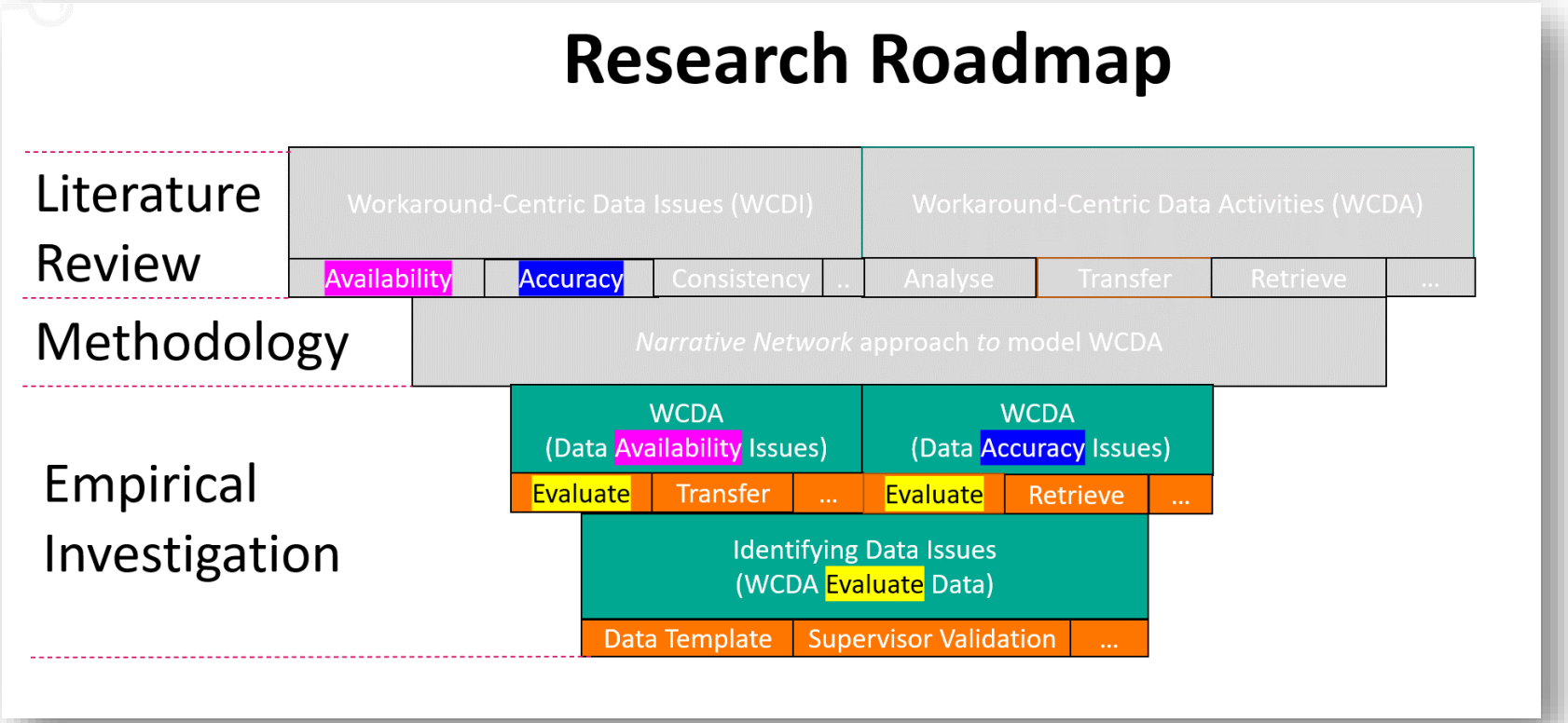

Figure 4.1 Research Roadmap: Empirical Investigation

Table 4.1 Addressing Data Issues - Planning Worksheet (Baird, 2021, p. 1207)

Item	Description	Details
Area of Theoretical Focus	What theoretical area is being targeted?	This study focuses on extending the *workaround* theory from three field studies. Mainly, it attempts to do this by inductively introducing six *patterns of action* (three for data accuracy and three for data availability) to mitigate data issues in centralised systems. Furthermore, it theorises how data broker employees *identify data issues* before data consumers use the data. It shows three approaches manifest in identifying data issues.
Theoretical Backgrounds	What common ground is relevant to this area, your goal, and your target audience?	Common Ground: In the workaround literature, this finds that *a workaround consists of a set of activities* (Haag et al., 2015) and should not be analysed as a single activity (Dunford & Perrigino, 2018). This research refers to this as *Workaround-Centric Data Activities* (WCDA). WCDA are a set of data activities inside a workaround. For example, consider an Electronic Health Record (EHR) that does not allow collaboration among physicians for patient treatment. To solve this collaboration

problem, a physician "*copies patient records*" onto a USB drive and *"sends it"* via email (Röder, Wiesche, & Schermann, 2014).

So, this workaround consists of two activities: *copies patient records* and *sends patient records.*

Research Objective: the research goal is to answer the following research question:
What are WCDA patterns of action to address data availability and accuracy issues?
How do data broker employees identify data issues?

Target Audience:

"Data Provocateurs":

A data provocateur is *"an individual who addresses data proactively, disrupts by advancing a data quality agenda, and challenges the status quo by questioning how they deal with data"* (Wibisono et al., 2022, p. 1).
So, following Redman (2016, p. 2)*: "everyone whose job depends on data"* must *"see themselves as a potential provocateur".*

Theoretical Tension	Why is a new theory needed?	Problematization (Alvesson & Sandberg, 2011; Sandberg & Alvesson, 2011). This study challenges a mainstream assumption in data governance research that addressing data issues is a *preventive* process. It shows that this process can be *curative* as well. Data governance research discusses various methodologies to address data issues (Batini et al., 2009; Nagle et al., 2020; Pipino et al., 2002; Sebastian-Coleman, 2013). However, mainstream research assumes that addressing data issues is *preventive*. Hence, it is pre-determined and top-down. For example, Batini *et al*. (2009) suggest two strategies for avoiding data issues: a *data-driven strategy* (e.g., acquisition of new data, record linkage, data and schema integration) and a *process-driven strategy* (e.g., process control, process redesign). (2002) *Preventive* assumptions can help formulate a comprehensive approach to data quality in data governance. However, they require a lengthy deployment time, careful monitoring, and post-deployment control. Infrastructure issues (Born &

		Krönung, 2016), lack of skilled people (Steinhueser et al., 2017), poor software functionality (Davison et al., 2019; Ibrahim et al., 2019), and poor software usability (Jagannath et al., 2019; van den Hooff & Hafkamp, 2017) can present challenges for an organisation. They can hinder organisations from producing quality data when needed. Worse, the pressing reporting needs of various stakeholders force operational employees to correct data issues once found (Wibisono, Sammon, & Heavin, 2022a). Therefore, the reality of addressing data issues is (actually) more *curative* than *preventive* (cf. Wibisono, Sammon, & Heavin, 2022a).
Resolution of theoretical tension	What is the primary aim of your theory paper?	This research aims to understand 1) patterns of action to mitigate data issues and 2) how data broker employees identify data issues.
	What theory building (or extending) the approach can be applied?	This study uses open coding and narrative network analysis to build the theory.

What is the condition under which you develop your theory?	Unit of Analysis (*addressing data issues*): In this case, the unit of analysis is *workarounds*. It chooses this approach because data activities and their contexts appear in the *workaround*. Unit of Analysis (*finding data issues*)*:* In this case, the unit of analysis is *data activities*. This study chooses this approach because data activities provide context to understand how employees identify data issues. The assumption for *addressing* data issues(s): 1. It assumes that every workaround needs data to materialise. So, every workaround must contain WCDA. 2. The workaround produces a single (type of) outcome. 3. A single event triggers the workaround: a data accuracy issue. Assumption(s) for *identifying* data issues: *1.* It assumes that the data's content is stable (not changing) during the examination.

	2. It assumes that humans (not machines) are central to identifying data issues. 3. It assumes humans use their subjectivity to examine data (Kooper et al., 2011). Other conditions It bounds the theorising to a workaround as part of organisational processes. These processes must perceive data as an integral part.
How can this work be extended?	This theory(ising) can be extended by asking the following research questions: WCDI: What are the positive impacts of workarounds on data? For example, are there any impacts on data availability, accuracy, completeness, and consistency? What are they? What specific aspect of workarounds data produce these positive impacts? WCDA: What are the relationships among WCDA? WCDA can construct a complex and interdependent web of data activities. Various network analysis parameters such as centrality, density, and cluster can be helpful (Pentland, 1999).

For example, centrality can help find the most "important" data activity across a web of data activities. This "important" data activity is now the bottleneck and can stop the critical business process from progressing. Therefore, identifying this "important" data activity can improve the flow of business process execution. As a result, understanding centrality can help organisations size workaround risks from a risk management perspective. Also, it can be beneficial in formulating more effective data governance programs.

WCDA: How do artefacts (e.g., formal and informal systems) enable and constrain WCDA? Research shows that artefacts can determine "*what information should be created, selected, and shared, with whom, in which format and in what sequence*" (D'Adderio, 2011, p. 216). Hence, they have a strong connection with data quality. However, the underlying mechanism that links certain WCDA artefacts and data quality is *unclear*. Here, the mechanism must explain "how and why" certain situations and events develop over time, subsequently affecting data quality. This understanding is essential to further inform IT designers to better cope with workaround-aware artefactual analysis, design, testing, deployment, use, and evaluation.

4.1 *Paper* 4: Data availability issues: decisions as patterns of action

4.1.1 Introduction

A data availability issue is when good quality data are unavailable when needed. Previous research suggests that the issue with data availability can cause organisational workarounds (Flanagan et al., 2013; Huuskonen & Vakkari, 2013; Reiz & Gewald, 2016). These workarounds are necessary to ensure that an organisation has good quality data for data-driven decision-making (Bozan & Berger, 2018).

4.1.1.1 Workarounds definition

Following previous literature reviews, this study defines workarounds as *adaptive processes* occurring when an organisation's centralised system does not provide decision-makers with 'good quality data. As a result, these decision-makers cannot commit to making an immediate data-driven decision. They may [i] delay their decision until "good quality data" are available. They may [ii] decide to use the "bad" data available. They may [iii] undertake a process to generate the necessary good-quality data (e.g., a workaround). So, the assumption that "good quality data" is always available in an organisation's centralised systems for data-driven decision-making is challenged.

Therefore, an employee retrieves data elsewhere, such as through outdated applications (Van de Weerd et al., 2019) or paper-based files (Drum et al., 2017). After that, the employee *processes and analyses* the data on a spreadsheet (Drum et al., 2016) before *uploading the data back* onto a centralised system (Davison et al., 2019). A workaround can have several data activities (e.g., *retrieve*, *process*, *analyse* and *upload* data). Therefore, to make "good quality" data available, a workaround typically has several data activities (e.g., retrieve, process, analyse and upload data). This research calls for such workarounds in workaround-centric data activities (WCDA) (Wibisono et al., 2020).

4.1.1.2 Workaround dilemma for organisations

As highlighted in the previous section, each data activity can link to other data activities and produce interdependent actions, which this study characterises as "patterns of action". These patterns of action represent potential pathways to overcome data availability issues. They help an organisation become more flexible in serving its diverse data needs. So, they are critical. However, while these patterns of action are necessary, ideally, they should not occur. While these patterns correct, repair, or compensate for a defect in another process that promptly fails to produce "good quality" data, they consume resources, e.g., employees' time and energy. Thus, the more complex the patterns of action, the more inefficient the organisation may be.

Therefore, workarounds, WCDA and their patterns of action introduce dilemmas for an organisation. Unfortunately, workaround research does not unpack these very well.

4.1.1.3 WCDA and Workaround Research

Despite this dilemma, workaround literature rarely discusses WCDA. Workaround literature tends to see WCDA and their patterns of action as a lesser aspect of workarounds. It associates WCDA with more general topics such as electronic health record (EHR) use (Blijleven et al., 2019; Ibrahim et al., 2019), information quality (Bozan & Berger, 2018; Drum et al., 2017; Myers et al., 2017), coordination (Eikey et al., 2015), enterprise architecture (Kopper et al., 2018), and information security (Silic & Back, 2014). Consequently, the understanding of WCDA remains limited. For example, what are WCDA characteristics? How are they linked to each other (as patterns of action)? Given this gap in the WCDA understanding, this research poses the following question:

RQ. What are the patterns of action triggered by data availability issues?

This study arranges the remainder of this research as follows. Section two discusses the research methodology. Next, section three describes the

analysis performed on the data, which results in the findings discussed in section four. Lastly, section five concludes the research.

4.1.2 Research Methodology

This section covers field study as research methodology, narrative networks for WCDA modelling, and the data analysis process.

4.1.2.1 Field Study

This research conducts a field study informed by (Eisenhardt, 1989) to address the research question. A field study is a common approach to studying workarounds. For example, previous research uses field studies to understand workarounds in a retail environment (Van de Weerd et al., 2019), health technology (Dunford & Perrigino, 2018; Jagannath et al., 2018), electronic health records (Ibrahim et al., 2019; Jagannath et al., 2018), and enterprise resource planning (Davison et al., 2019).

This study conducts a field study from June to August 2021 in an Indonesian plantation company producing sugar. The company was founded in 1996. As of 2018, it employs approximately 14,083 employees. The company includes nine major sugar factories across cities in the East Java Province of Indonesia. This study collects data from the head office's quality assurance (QA) unit to investigate how and why workarounds emerge in critical business processes.

The QA unit has two sub-units: on-farm and off-farm. The on-farm unit is responsible for checking the security of sugarcane supplies from independent farmers and fields held by the factory. This sub-unit captures ongoing factors that can hinder the quality and quantity of sugarcane supplies. For example, each field provides several data points, such as sugarcane plantation qualities, soil quality, rainfall rate, and pest and weed volumes. These data points present an early warning system for incoming production.

Moreover, the off-farm unit ensures the quality of the manufacturing process. It checks the daily preparation or execution of sugar production across all the sugar factories. For example, it collects and analyses changing real-time

data in the factory as a work progress report (e.g., reactor's acidity and temperature).

The company employs two disconnected centralised systems (e.g., SAP and e-Farming) with countless decentralised systems (e.g., spreadsheets). Thus, critical data are unavailable when needed, especially for analysis and reporting. For example, the board of directors demands daily production reports to assess the company's production health every morning. Unfortunately, SAP cannot provide these data on time. So, the QA unit has devised three "workaround" strategies to solve this problem. First, it collects field data by randomly visiting sites as needed. Second, it retrieves daily data for analysis (e.g., work progress reports from the sugar factory employees). Third, it collects data from third parties (e.g., satellite data to measure the actual area of the sugarcane fields).

Table 4.2 Interview Respondents

No	Respondent	Organisation Role	Sub-unit	Responsibility	Years in Service
1	H1	Head of Affairs	Off-farm	Managing the operations of off-farm units	8 years
2	B1	Business Assistant	Off-farm	Analysing and reporting data	5 years
3	B2	Business Assistant	On-farm	Analysing and reporting data.	10 years
4	B3	Business Assistant	On-farm	Monitoring the progress of sugarcane fields	15 years
5	J1	Junior Business Assistant	Off-farm	Compiling and preparing data for further processing	17 years
6	J2	Junior Business Assistant	On-farm	Analysing data for making reports	7 years

.

Table 4.3 Four steps in constructing a NN.

No	Step	Note	The application
1	Choose a process and define its boundary	Focus on "purpose."	Purpose: WCDA to deal with issues with data availability
2	Adopt a point of view	Rule 1. A narrative fragment must come from a process actor.	Process actors were employees in the QA unit
3	Collect the narratives and code the fragment	Rule 2. A narrative fragment has three attributes: actor, action & resource	This study conducts interviews and extracts narrative fragments from the narratives. It uses a *subject-verb-object* pattern to extract narratives. An example of how It extracts the narratives is available in Table 4.4.
		Rule 3. All attributes in a narrative fragment establish the action type	It uses three attributes (actor, action, and resource) to decide whether a narrative fragment is of workaround
		Rule 4. A narrative fragment must contain a data activity.	It only models' action that is of data activity (e.g., store data, retrieve data, transfer data)
		Rule 5. A narrative fragment data activity must follow a standard naming convention	It uses open coding for generalisation. Hence, it can make a standardised naming for all actions.
4	Relate code with sequences	Visualise the NN – to establish a pattern of action	It links each data activity and establishes a pattern of action.

Regardless of its strategy, the QA unit must ensure that the obtained data are "appropriate" for use. For example, the QA unit must compare the data with other sugar factories when analysing a submitted work progress report (as a spreadsheet) from a sugar factory. Suppose there are “abnormalities” in the spreadsheet. In that case, the QA unit returns the spreadsheet for revision (e.g., missing columns, submitting wrong spreadsheet versions). This process continues until there is no abnormality in the data. If there are differences between satellite data and SAP/e-Farming data, the QA unit visits the site to settle any differences. Therefore, the company can have “quality” data available somewhat timely.

Moreover, although the QA unit is critical for the company, the unit employs very few people (e.g., seven employees). This study interviews six respondents, who are all QA unit staff. One respondent works as the Head of Affairs, three as Business Assistants and two as Junior Business Assistants (see Table 4.2 for respondent details). Every respondent has worked for the QA unit for more than five years.

The online semi-structured interviews last between 45 and 60 minutes. All interviews are conducted in Indonesian and Javanese, recorded and later transcribed into English. Each interview follows predefined interview guidelines. Most importantly, it focuses on operational employees who execute processes daily (and are familiar with the workarounds). An interview guide establishes how QA unit employees work, what data they need, and how they are furnished with that data. After generating the interview transcripts, this study analyses them using a Narrative Network (NN) approach.

4.1.2.2 Modelling WCDA using the NN approach.

This research leverages the rules for modelling using the NN approach proposed by (Wibisono, Sammon, & Heavin, 2022c) to model WCDA. Table 4.3 provides an overview of these WCDA modelling rules and how this study applies these rules in the sugar plantation context. There are four steps in constructing narrative fragments (e.g., the atomic block of a NN): 1) Choose a process and define its boundaries, 2) Adopt a point of view, 3) Collect the narratives and code the fragment, and 4) Relate a code with sequences.

First, this research selects QA unit employees that enact WCDA (Rule#1: A narrative fragment must come from a process actor). Second, all narratives are classified into three broad categories: subject (actor), verb (action), and object (resource) (Rule#2: a narrative fragment has three attributes: actor, action, and resource). Third, we identify whether an action is a workaround by evaluating the other attributes (actor and resource) (Rule#3: all attributes in a narrative fragment establish the action type). Fourth, a workaround can contain a non-data activity also (Rule#4: A narrative fragment must contain a data activity). Hence, it models data activities. Finally, it uses an open coding approach to satisfy the fifth rule (a narrative fragment data activity must follow a standard naming convention). The detail of how it progresses the generalisation is available in Table 4.4 and Table 4.5

4.1.3 Data Analysis

This study uses open coding for analysis (cf. Corbin & Strauss, 1990). The coding ensures that each narrative fragment has a standardised label for each component (e.g., actor, action, and resource). Thus, researchers can extract each data activity and corresponding actor consistently and clearly. Similarly, researchers can better analyse patterns of action as standard labels allow for easier comparison between the data activities of each actor. For an example of open coding, see Table 4.4 and Table 4.5.

This research identifies two actors during open coding: QA unit staff and sugar factory staff. Here, each actor represents the unit where the employee works. Each employee's formal responsibilities do not represent what each employee does in fixing data availability issues. Each employee seems capable of completing all data tasks. So, this research does not distinguish the actor based on their formal responsibilities.

Given the appreciation of the role played by the QA unit, the QA unit employees send data to stakeholders such as the board of directors (BoD), government agencies, financial units, plantation units, and sugar factory managers. This data originates in each sugar factory and is sent by sugar factory employees to the QA unit for analysis and use in reporting.

.

Table 4.4 The Text Exemplars for Final Management Reporting

No	Sample extracts from interviews	Actor		Action		Resource	
		1st Order	2nd Order	1st Order	2nd Order	1st Order	2nd Order
1	My task is to retrieve data from all units.	My	QA unit employee	Retrieve	Retrieve	Data	(*Data*) Main Production
2	From the data I retrieve, I compile them	I	QA unit employee	Compile	Compile	Data	(*Data*) Main Production
3	Then the next step (the data) is filtered by me (using Microsoft Excel).	Me	QA unit employee	Filter	Evaluate	MS. Excel	Spreadsheet
4	We issue a daily production report. In this case, the content is about the main production.	We	QA unit employee	Issue	Transfer	(*Data*) Main Production	(*Data*) Main Production
5	Then, the data are checked by my supervisor (using Microsoft Excel).	My supervisor	QA unit employee	Check	Evaluate	MS. Excel	(*Artefact)* Spreadsheet
6	Next, I send the report to those in unit groups	I	QA unit employee	Send	Transfer	Report	(*Data*) Main Production
7	By the unit, the report is evaluated and stored. When an irregularity is found, these employees let me know.	The unit	Sugar factory employee	Evaluate	Evaluate	Report	(*Data*) Main Production

9	By the unit, the report is evaluated and stored. When an irregularity is found, these employees let me know.	The unit	Sugar factory employee	Store	Store	Report	(*Data*) Main Production
10	By the unit, the report is evaluated and stored. When an irregularity is found, these employees let me know.	They	Sugar factory employee	Let me know	Transfer	Report	(*Data*) Main Production
11	(If there is an irregularity) I see the data in it. So (I know) where the mismatch is	I	QA unit employee	See	Evaluate	Data	(*Data*) Main Production
12	If the discrepancy can be tolerated, I ask each unit to make corrections (by using WhatsApp)	I	QA unit employee	Ask to correct (data)	Request for Action	WhatsApp	(*Artefact*) Instant Messaging
13	Then the unit also makes corrections. (So), the data can remain the same for all stakeholders.	The unit	Sugar factory employee	Correct	Correct	Data	(*Data*) Main Production

The analysis reveals seven data activities: *retrieve* data, *compile* data, *transfer* data, *evaluate* data, *store* data, *correct* data, and *request for action* (see Table 4.4). *Retrieve* data are an activity where an employee collects data from various sources. For example, a QA unit employee collects data from the sugar factory. In contrast, a sugar factory employee collects data from its sources (e.g., machines in the factory). Both employees collect previous operations data from two centralised systems for further analysis (e.g., SAP and e-Farming). This data activity always facilitates the next data activity to emerge.

Compile data means an employee combines all obtained data into one spreadsheet for analysis, checks for missing data, and arranges them into an acceptable spreadsheet format. Hence, the data can be used in further processing.

Transfer data encompasses two types of activity. First, it includes any activity that transfers data from one system to another, for instance, transferring data by sharing a spreadsheet via WhatsApp. Second, it encompasses any activity that disseminates data to stakeholders. For example, a QA unit employee may present to the board of directors, report data to government agencies, or provide factory managers with feedback.

Evaluate data ensures that the data are appropriate (stable). It includes several data activities such as checking, analysing, summarising, and calculating data. *Evaluate* data are critical for the factories as this activity ensures that the data are relevant for reporting.

Correct data is an activity to modify the data either in a centralised system (e.g., SAP ERP) or a decentralised system (e.g., spreadsheets). It aims to ensure that the data in the corresponding system is correct and ready for further processing or transfer to other parties.

Store data is an activity to store data for the first time. It includes entering new data (for the first time) on centralised or decentralised systems. Store data are mandatory to ensure that data are available and retrievable. Without this data activity, it is impossible to complete further data processing.

The last data activity is a *Request for Action*. This activity is exclusive to the QA unit. This activity recommends that the sugar factory "does something" regarding the data. For example, the QA unit requests that the sugar

factory stores new data in the spreadsheet whenever the data are missing. The activity also includes a periodic request to 'transfer data'. After open coding, this study transforms the result into a NN for further analysis (see Figure 4.2). The following section discusses the findings.

4.1.4 Findings and Discussion

The sugar plantation company established the QA unit as a unique unit at its head office. This unit is pivotal in addressing the Board of Director (BoD)'s needs to ensure quality production. It supplies essential data and helps BoD to gauge what is happening. For example, the QA unit predicts crop failures due to decreased precipitation or the spread of uncontrolled weeds and pests.

Therefore, a QA unit employee must double-check the data before inputting them into SAP to achieve this goal. Otherwise, the QA unit must correct the data, which is lengthy and time-consuming. If this situation happens, data availability issues occur. Hence, SAP cannot provide real-time data when needed by BoD.

To avoid this situation, employees execute several processes. First, the QA unit employee requires that each sugar factory submits a daily work progress report (as a spreadsheet) before 10 am via email. The spreadsheet contains several daily parameters. To prevent sending failure, a sugar factory employee must submit some essential parameters before 7 am daily. The QA unit employees can assess the data quality from these data. Also, they can generate responsive reports for various stakeholders (e.g., BoD, government agencies, and other units) before the data are available on SAP. Submitting these data also helps sugar factory employees enter the "right data" into the centralised systems later. Therefore, the company can avoid issues with missing data.

The story begins with Employee J1 (off-farm), who proactively contacts each sugar factory employee to submit a work progress report in the morning (see Figure 4.2). Next, each sugar factory employee sends the spreadsheet to Employee J1. Afterwards, Employee J1 compiles the data into one spreadsheet and transmits it to Employee H1 and Employee B1 for evaluation. Employee

H1 and Employee B1 evaluate the spreadsheet to find errors. If there is an error, they contact the sugar factory employee to fix it. They show which parts of the data are suspicious. Next, an employee in the sugar factory rechecks the data. The employee retrieves data from the field, evaluates them, corrects them, and transfers them to the QA unit. In cases where the sugar factory employee cannot fix the data, a QA unit employee visits the sugar factory to retrieve the data.

The complete narrative of this process is available in the appendix. This research identifies three patterns of action in dealing with data availability issues: *dual inspection, prudent control,* and *mindful handling*.

4.1.4.1 Pattern #1: Dual Inspection

Dual inspection occurs when two WCDA activities: *"evaluate data"* and *"transfer data",* are repeatedly executed as a pair (see Figure 4.2). In this pattern, an employee in the first pair does not possess the knowledge (or skill) to deal with existing data abnormalities or data analysis requirements. So, another employee must execute the second pair.

As a pattern, dual inspection is inefficient because it repeats the same data activities several times. Over time, it increases operational costs and wastes employee time. However, as many employees scrutinise the same data, this pattern can help identify issues across large data silos. This pattern enables an organisation to identify the right employee to handle data at the right time. For example, an employee frequently involved in this pattern is knowledgeable about data. Hence, this employee is the best option to fix data availability issues.

4.1.4.2 Pattern #2: Prudent Control

Prudent control is a triangular pattern where "*evaluate data*" (QA unit) is followed by "request for action" (QA unit) and "correct data" (Sugar Factory). It imposes a specific order between the QA unit and a sugar factory by reducing and regulating conflicts triggered by data issues.

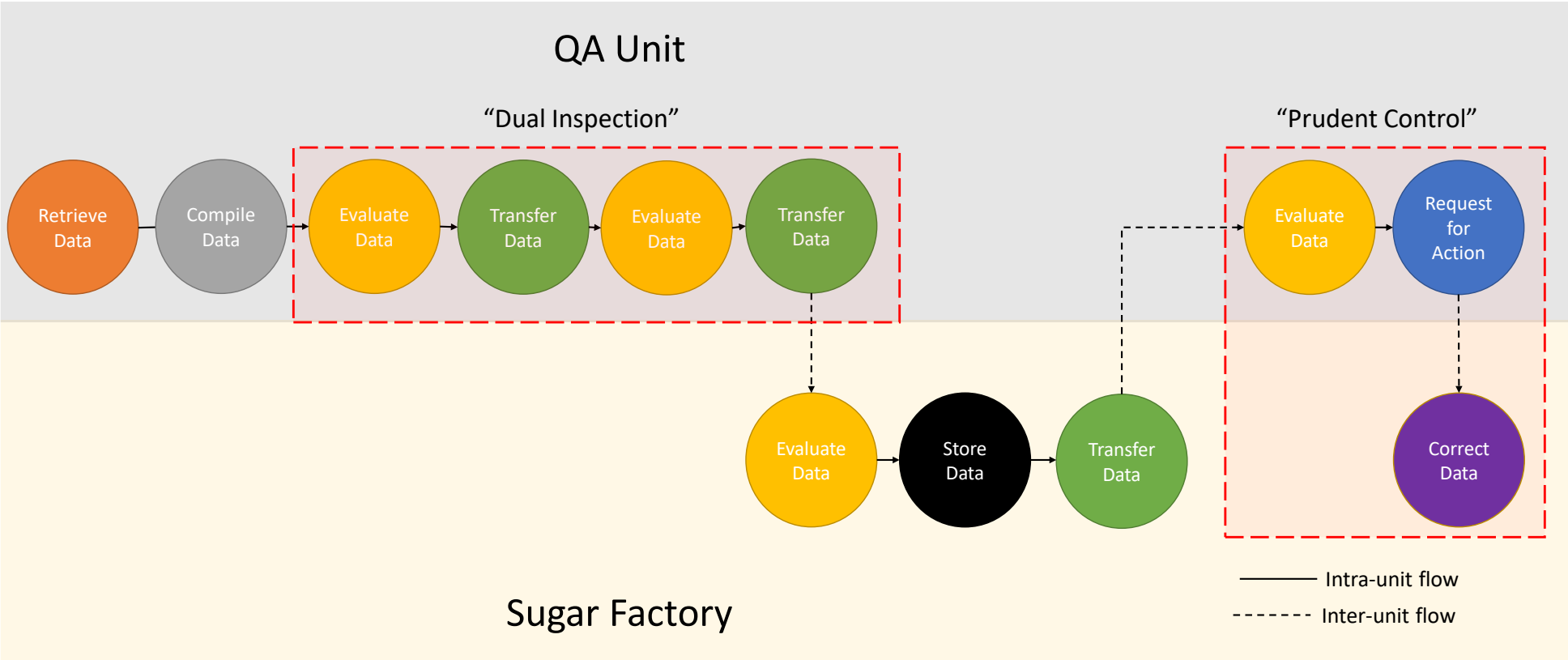

Figure 4.2 Narrative Network for Final Management Reporting.

This action requires the QA unit to coordinate with the factory when fixing the data. Thus, it requires additional time, mainly because the QA unit employees and sugar factory employees prioritise data issues differently.

Furthermore, poor internet access speeds can be an extra challenge to processing times. However, this pattern enables the sugar factory to appreciate and fix its data issues. It delegates data ownership to the factory as the data provider. Therefore, this pattern limits the impact of data issues to a single factory (out of the nine factories). In practice, this pattern improves the speed of data access. Also, correcting data promotes data consistency across various data records maintained by the factory. Therefore, this pattern is essential for data governance, specifically by establishing effective rules and policies.

4.1.4.3 Pattern #3: Mindful Handling

Mindful handling is a pattern where the "evaluate-retrieve-evaluate-correct" pattern occurs (see Figure 4.3). It enables employees to act and reflect on what is going on. The first WCDA of "evaluate data" allows one to make sense of the problem and produce a plausible plan for correction. After that, "retrieve data" permits accessing the original data source to address the problem while maintaining data quality. Next, the second "evaluate data" enables one to reflect on the action, seeking to understand whether previous data activities have resolved the problem. Finally, "correct data" is the data activity to enact mindful changes to the data.

On the one hand, mindful handling can be challenging. Many distractions can occur if the time between doing (e.g., retrieve, correct) and reflecting (e.g., evaluate) is considerable. These distractions reduce the feeling of order, clarity, and rationality in subsequent data activities. Thus, producing another data issue.

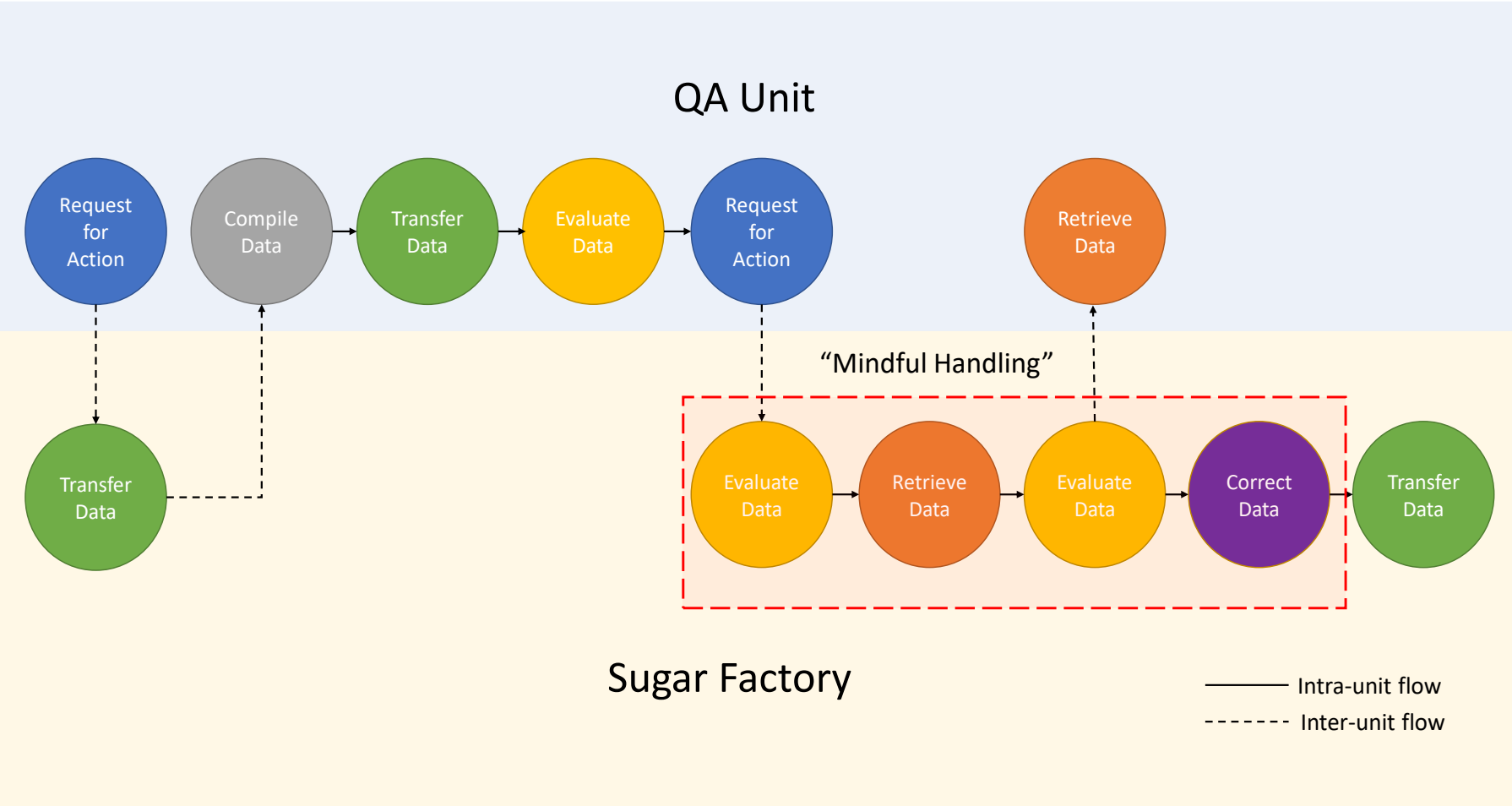

Figure 4.3 Narrative Network for Collecting Daily Production Data

On the other hand, mindful handling can be beneficial if employees are responsive to this pattern. It allows employees to comprehensively reflect on the uncertainty and ambiguity of data by establishing rational explanations of the environment. This explanation facilitates retrieving the “good quality” data for their sources. Hence, it can provide a thorough and accurate fix for data issues. This action is crucial for data governance programs to minimise data-related costs and risks.

4.1.5 Conclusion

This study examines WCDA as a set of patterns of action by conducting a field study in a sugar plantation company based in Indonesia. It uses the NN approach to generate and visualise each employee’s process understanding. Employees often use different expressions to describe the same thing using open coding.

This research can standardise the labels used in each narrative fragment. It finds seven WCDA: retrieve data, compile data, transfer data, evaluate data, store data, correct data, and request for action. It visualises three patterns of action to deal with data availability issues: dual inspection, prudent control, and mindful handling. Both advantages and disadvantages of these patterns are discussed in the context of data governance.

4.1.5.1 Theoretical Contributions

This research leads to new insights relevant to workaround literature, particularly WCDA as an organisational phenomenon. This study demonstrates the NN approach's use to visualise patterns of action by identifying seven WCDA and three patterns to fix data availability issues. Therefore, it advances the understanding of WCDA and their relationships, elevating the significance of WCDA that previous workaround research has overlooked. Thus, the theoretical contribution is clear and substantial for workaround and data governance research.

4.1.5.2 Managerial Implications

The managerial implications are most relevant for aspiring data-driven organisations that run multiple centralised and decentralised systems to support their operations. Furthermore, the transformation to a data-driven organisation has become more prevalent. Consequently, multiple system landscapes propagating data availability issues can force employees to execute WCDA to meet their "good quality" data needs. In this regard, this study raises awareness of data availability issues in aspiring data-driven organisations.

As for recommendations, this research suggests that every organisation automates (real-time data entry) repetitive and predictable processes by using IoT and sensors. However, if human action for data entry is required, this study suggests the organisation enhance employee data discipline. One strategy is to incentivise employees to enter data on time. By doing so, data availability issues can be avoided.

Further, WCDA and the associated patterns of action for dealing with data availability issues are reminiscent of a hidden data factory. The hidden data factory describes necessary rework as an ongoing reactive approach to address data quality issues within an organisation's centralised system(s). So, one can see WCDA patterns of action as an organic data governance approach. It helps the organisation identify data needs across units and their tools, data sources, providers, and users. However, this information often disappears because employees do not visually model the hidden data factory. As a result, the footprint (e.g., tools, actors, step-by-step) in how employee "process data" is missing. Therefore, managers must train their employees to visually model WCDA (Wibisono, Sammon, & Heavin, 2022c) and use it in their work.

Modelling WCDA can help an organisation build a plausible picture of data governance. For example, it has a better conversation about managing data and by whom. Why do specific data issues materialise while some others do not? What are the causes? This understanding can improve data-related process transparency, directly impacting data quality. Subsequently, these insights can inform managers in improving data governance initiatives. Hence, they can increase data values and minimise data-related costs and risks as time passes.

4.1.5.3 Limitation and Further Research

There are several limitations to the study. First, the patterns of action come from the QA unit only and not the sugar factories. Consequently, there is a possibility that the shape of other patterns of action can be more complex to theorise. This study blacks-boxes the process from the perspective of the nine sugar factories. So, the emerging patterns of action are more straightforward to analyse as it continues to unpack WCDA.

Second, all patterns of action represent *ostensive* dimensions (Feldman & Pentland, 2003) (not *performative*). As part of *ostensive* dimensions, these patterns may not reflect the actual actions of employees. However, they reflect how employees generally perceive how to do their tasks. Research indicates that perception is always less complex than actual actions (Feldman & Pentland, 2003). So, the introduced patterns of action tend to be parsimonious. This feature is essential to capture only the most critical elements of the phenomenon (e.g., WCDA). Therefore, it can produce a better theory (Suddaby, 2010).

Further research can examine patterns of action produced by other data issues: data accuracy, duplication, access, completeness, privacy, meaning, and leakage. This examination can assess which data issues produce the most complex patterns of action. Later, future research can isolate similar patterns across data issues as a starting point for developing a better approach to coping with data issues and WCDA. Also, data proliferation has now become more observable in many organisations. Future research can investigate emerging patterns of action better to manage data issues in such a data flood.

Overall, the ambition remains to imagine if an organisation can manage data issues and WCDA to prevent patterns of action from replicating and growing uncontrollably, thus avoiding the emergence of hidden data factories. The next chapter discusses *patterns of action* related to another data issue: data accuracy.

4.1.6 Appendix

Table 4.5 The Text Exemplars for Collecting Daily Production Data

No	Sample extracts from interviews	Actor		Action		Resource	
		1st Order	2nd Order	1st Order	2nd Order	1st Order	2nd Order
1	So, whenever it is 7 AM, I call the factory—asking them to send their reports quickly.	I	QA unit employee	Call Out	Request for Action	Data	(*Data*) Main Production
2	At 10 AM, they transfer everything via email.	They	Sugar factory employee	Transfer	Transfer	Everything, Email	(*Data*) Main Production (*Artefact)* Email
3	I compile all data that I get.	I	QA unit employee	Compile	Compile	Data	(*Data*) Main Production
4	After the report has been collected, we check. Is there any mistake?	We	QA unit employee	Check	Evaluate	Report	(*Data*) Main Production
4	If the discrepancy is tolerable, we ask them to correct the data	We	QA unit employee	Ask them	Request for Action	It	(*Data*) Main Production
5	Then the report is evaluated by the sugar factory	Sugar Factory	Sugar factory employee	Evaluate	Evaluate	Report	(*Data*) Main Production

6	(If there is a problem) they look for the data that are in the machines.	They	Sugar factory employee	Look for	Retrieve	Data	(*Data*) Main Production
7	Next, they calculate the deviation (in the data) after cross-checking.	They	Sugar factory employee	Calculate	Evaluate	Data	(*Data*) Main Production
8	Yes, their solution is to change the data in the spreadsheet.	Their	Sugar factory employee	Change	Correct	Data, Spreadsheet	(*Data*) Main Production (*Artefact)* Spreadsheet
9	They have to resend all data from the wrong day to today.	They	Sugar factory employee	Resend	Transfer	Data	(*Data*) Main Production
10	(If there are still problems) That's when we get down to supervision. Check the field.	We	QA unit employee	Check the field	Retrieve Data	Data	(*Data*) Main Production

4.2 *Paper* 5: Values-driven workarounds to address data accuracy issues: Theorising from Indonesian field studies

4.2.1 Introduction

Data accuracy issues are where the available data do not represent reality (NCES, 1997, p. 45). They are real problems for businesses. For example, MIT Sloan state that employees can spend half of their time dealing with data quality issues (including accuracy) (Lepeniotis, 2020). Data quality issues (e.g., data accuracy) impose a $600 billion cost annually on the US Economy (Emeka-Nwokeji, 2012). It can be 10% of the organisation's revenue, not to mention the extra cost incurred to correct and verify these data (Emeka-Nwokeji, 2012). Subsequently, data accuracy issues can engender missed opportunities, lost customers, and misleading insights for decision-makers and stakeholders.

Employees execute connected workaround-centric data activities (WCDA) as a pattern of action to solve data accuracy issues. These activities work as a *pattern of action* to fix data (Wibisono, Sammon, & Heavin, 2022a). This pattern of action proves to be dilemmatic for organisations.

On the one hand, this pattern is a workaround for another "failed" process. It consumes resources (e.g., employees' time and efforts) to fix data issues that should not occur in the earlier process. Hence, this pattern demonstrates operational inefficiencies.

On the other hand, this pattern helps an organisation identify and mitigate data accuracy issues. Therefore, it enables an organisation to meet its data needs and reporting requirements. Also, it improves information flow in later processes, especially processes that consume the corrected data. Therefore, this pattern is critical.

Despite this dilemma, workaround research does not unpack WCDA very well. It sees WCDA as trivial elements of a workaround. Consequently, it discusses WCDA under different research focus. For example, information quality (Bozan & Berger, 2018; Drum et al., 2017; Myers et al., 2017),

electronic health record (EHR) use (Blijleven et al., 2019; Ibrahim et al., 2019), information security (Silic & Back, 2014)., enterprise architecture (Kopper et al., 2018), and coordination (Eikey et al., 2015). Consequently, the WCDA understanding remains under-researched. For example, what are WCDA? How do they relate to each other (as patterns of action)? How do data accuracy issues influence WCDA and their pattern of action?

Moreover, Indonesia is the largest nation and economy in ASEAN. As a result, every organisation operating in Indonesia must embrace digital transformation to be competitive (Das et al., 2016). The problem is that digital transformation is not always as expected for organisations. Infrastructure problems, software failures, and data quality issues can drive employees to execute workarounds to accomplish tasks (Alter, 2014). As Javanese people comprise the largest population in Indonesia's workforce, understanding their values is beneficial for understanding "local WCDA" in an organisation.

Furthermore, by theorising WCDA, this study addresses a research call made by Ejnefjäll & Ågerfalk (2019). They suggest that despite workarounds being a multifaceted phenomenon, they are "*surprisingly under-investigated and [under] theorised*" (2019, p. 341). Drawing on the Javanese context, it attempts to "*offer a better explanation of behaviour at the local or indigenous level*" (Davison & Díaz Andrade, 2018, p. 761). Therefore, for these reasons, this study poses the following research question:

RQ. How do Javanese values drive WCDA patterns of action to address data accuracy issues?

The research introduces several theoretical contributions for workaround research. First, this study challenges the mainstream understanding that a workaround is an atomic and non-divisible process (Koppel et al., 2008; Vogelsmeier et al., 2008). It shows that a workaround can contain data activities in a more granular form. Second, it leverages the understanding of WCDA and their relationships (as patterns of action).

Furthermore, the target audience is roles responsible for managing organisational data. They can be formal roles in data governance, such as data

stewards, data councils, or data governors (Plotkin, 2014; The Data Warehousing Institute, 2010; Vojvodic & Hitz, 2019). They can also be emerging roles such as *data provocateurs* (Redman, 2016a, p. 2). As data-driven organisations become prevalent nowadays, these roles are indispensable to governing data. Among these roles, the primary audience is *data provocateurs* because many organisations do not have a clear data governance structure and control (Janssen et al., 2020).

This study defines a data provocateur as *"an individual who addresses data proactively, disrupts by advancing a data quality agenda, and challenges the status quo by questioning how they deal with data"* (Wibisono, Sammon, & Heavin, 2022c). Following Redman (2016a, p. 2)*: "everyone whose job depends on data"* must *"see themselves as a potential provocateur".*

In Section 4.2.3, this study provides a detailed account of our research methodology, with a particular focus on data gathering in Section 0. Our data analysis process is explained in Section 0, while our findings and accompanying discussion are presented in Section 4.2.5. Lastly, Section 4.2.6 concludes the study.

4.2.2 Theoretical Background

This section explains some concepts that this research uses to address research questions, such as Workaround-Centric Data Activities (WCDA) and the Javanese values of Kekeluargaan (e.g., *bapakism*, *rukun*, *musyawarah mufakat*, and *gotong royong*).

4.2.2.1 Workaround-Centric Data Activities (WCDA)

Workaround research is a growing and maturing domain (Alter, 2014). It is prominent in post-adoption behaviour literature (Zamani & Pouloudi, 2020). However, most workaround research assumes that a workaround is: 1) a composite, atomic, and non-divisible process and 2) an isolated chain of action.

Koppel et al.(2008) investigated workarounds in Barcode Medications. They show some "atomic" workaround examples such as "User scans medication from the patient drawer without visual check" or "User administers

medication without scanning patient ID". These examples show a workaround as an atomic and isolated object. Vogelsmeier et al. (2008) made improvements to examples. They have shown a workaround as two connected actions. However, each action is not atomic enough. For example, "prepare to fax printed orders to pharmacy". In this case, "prepare" can be split into more atomic operations, such as *retrieving* the data from the shelf and *storing* them in a folder.

Moreover, these two assumptions prove problematic. Researchers cannot explain why two seemingly identical workarounds can produce different consequences. Consider two workarounds with the same label: "*a physician analyses patient's data from the centralised system at home*" (Röder, Wiesche, & Schermann, 2014).

The first workaround can be for the physician *to download* and *send* the data to other physicians using the office's email. Therefore, they can analyse the result at home (Röder et al., 2015). The second workaround can be for the physician to *download* the data, *store* data on a USB stick, and bring it home (Silvius & Dols, 2012). As a USB stick can vanish (e.g., theft or dropped somewhere), the organisation can become vulnerable to data security and protection policy breaches.

The concept of WCDA (Wibisono et al., 2020; Wibisono, Sammon, & Heavin, 2022c) attempts to challenge these two assumptions (e.g., atomic and isolated). Instead of adhering to these two assumptions, this study opens the workaround's black box. It argues that two or more atomic activities (e.g., WCDA) link like a chain and establish a workaround. Research needs to open the workaround’s black box to uncover underlying mechanisms in a workaround that directly affect organisational data. This understanding is pivotal to comprehending how workarounds impose data-related risks and opportunities on organisations.

At present, organisations are striving to be more data-driven than ever. Therefore, various dimensions of data (e.g., quality, velocity) are deemed necessary. So, introducing WCDA can benefit data provocateurs because they oversee data as organisational assets. They are not passive users like they once may have been. WCDA can help data provocateurs formulate a comprehensive

strategy to navigate workarounds. For example, they establish data accountabilities, promote their data oversight, and improve data protection.

4.2.2.2 WCDA and Javanese-driven Indonesian Values

Research has shown that an employee's values, such as work ethic, can trigger a workaround (Azad & King, 2012). For example, physicians may skip entering data during a patient consultation. One reason is that they believe patient safety is the top priority rather than inputting data into the Electronic Health Record (Blijleven et al., 2019). Consequently, an employee's values can positively or negatively impact the outcome of a workaround, affecting the organisation (Azad & King, 2012). For instance, data availability or timeliness issues can arise if data are not entered on time.

Therefore, this research investigates how Javanese-driven Indonesian values impact a specific workaround: workaround-centric data activities. Understanding these values is crucial, considering Indonesia's significant economic presence in the ASEAN region, with Javanese people constituting the largest workforce in the country. By understanding their values, researchers can gain insight into how employees manage data, leading to a better understanding of managing data-related workarounds more effectively.

4.2.2.3 Kekeluargaan as Javanese-driven Indonesian Values

Kekeluargaan (familyism) is a Javanese value for kinship. It has informed Indonesian values (Hermawan & Loo, 2019; Magnis-Suseno, 1997). It is an umbrella concept that facilitates other Indonesian values. For example, *bapakism* (paternalistic leadership), *rukun* (harmony), *musyawarah mufakat* (collective and unanimous), and *gotong royong* (mutual aids) (Hermawan & Loo, 2019). *Kekeluargaan* suggests that people cannot (living) alone. So, they must expect help from others, especially relatives. Simultaneously, they must acknowledge that others expect the same from them.

Following this view, people must pay attention to others' needs. Therefore, it is common for Javanese to "*treat people with whom they have a business or personal relationship as relatives by blood*" (Hermawan & Loo, 2019, p. 2). People must maintain *uniformity* and *harmony* (Hermawan & Loo,

2019). These values contribute to a life of harmony, avoiding conflict where possible. As an umbrella concept, *kekeluargaan* comprises four sub-concepts: *bapakism*, *rukun*, *musyawarah mufakat*, and *gotong royong*.

4.2.2.4 Bapakism (Paternalistic Leadership)

Bapakism is a personalised leader-follower group (Robison, 1981). It works like a father (leader) and a child (follower) (Hermawan & Loo, 2019) in a family (Robison, 1981). The leader and his children cannot quit their positions (Robison, 1981). They must work in a reciprocal relationship over time (Hermawan & Loo, 2019). As a *Bapak* (father), the leader assumes a leading role. He may be someone who founded the organisation. Otherwise, he serves the longest time in the organisation or holds the most senior position.

As a *Bapak*, he has power, authority, and legitimacy (Hermawan & Loo, 2019) in formal and informal groups (Irawanto, 2018). His authority is indivisible, non-transferable, and eternal (Kahane, 1984). Therefore, to be balanced, as a child, the follower must demonstrate constant respect, obedience, and loyalty toward the *Bapak* (Hermawan & Loo, 2019; Irawanto, 2018). Followers can come from various "sources": younger, a junior in work status, or anyone with lower status. These followers should not question Bapak's decisions under any circumstances. So, *bapakism* is a form of blind loyalty to a higher authority (Irawanto, 2018).

4.2.2.5 Rukun (Harmony)

Rukun is a situation where harmony materialises by avoiding disputes and conflicts (Magnis-Suseno, 1984). It regulates social relationships on the surface, even though it may not solve any underlying problems that hamper them (Magnis-Suseno, 1984). Each individual must respect another's thoughts (Hermawan & Loo, 2019). A request cannot be rejected at once. People help each other without ulterior motives (Hermawan & Loo, 2019). People should move in groups and not individually. For example, taking a "more" advanced position is inappropriate, even though the move benefits the group (Magnis-Suseno, 1984). Consequently, people can maintain harmonious lives (Magnis-Suseno, 1984).

4.2.2.6 Musyawarah Mufakat (Collective and Unanimous)

Musyawarah mufakat comprises two concepts: musyawarah and mufakat. *Musyawarah* is a consultation (Allen & Allen, 2016), reflecting collective deliberations (Collins, 2004). *Mufakat* is a unanimous consensus (Collins, 2004) and is the product of *musyawarah* (Collins, 2004; Hermawan & Loo, 2019; Magnis-Suseno, 1997). The objective of musyawarah mufakat is to gain consensus from all organisation members (Hermawan & Loo, 2019). Musyawarah mufakat considers all members' views. No decision is made to benefit one party (Hermawan & Loo, 2019). During the consultation, members must be willing to be tolerant, by compromise, of all particular views (Magnis-Suseno, 1997).

4.2.2.7 Gotong Royong (Mutual Aids)

Gotong Royong is mutual assistance (Bowen, 1986; Mulder, 2005; Sullivan, 1986). It views collective life as crucial (Bowen, 1986). Therefore, it equally shares burdens and benefits across all organisation members (Hermawan & Loo, 2019; Sullivan, 1986) as a moral obligation (Bowen, 1986). It is a balanced mutual and reciprocal arrangement (Bowen, 1986). For example, if you need bread (today) and someone gives you one piece of bread, then (someday) you must provide another in return when needed.

Gotong Royong produces good relationships among organisation members by showing empathy (Magnis-Suseno, 1997). It promotes the general ethos of selflessness for the common good (Bowen, 1986). Also, it encourages the absorption of workforce surplus and promotes workload distribution during workforce deficit (Kahane, 1984).

4.2.3 Research Methodology

This section discusses the research design of this study. Also, it explains the narrative network as a tool for data analysis.

4.2.3.1 Field Studies

Given the purpose of the work, it conducts field studies across three Indonesian entities (e.g., a plantation company, a government agency, and a

university). These field studies examine some WCDA scenarios across differing contexts. Each case represents a specific reporting term for the main stakeholders: plantation company (daily), government (annually), and university (one academic cycle: 1-6 years). The three research sites represent data accuracy issues from their respective data realities.

Field studies are a popular choice when examining workarounds. Previous research using field studies to investigate workarounds include studies focusing on enterprise resource planning systems (Davison et al., 2019), health technology (Dunford & Perrigino, 2018; Jagannath et al., 2018), electronic health records (Ibrahim et al., 2019; Jagannath et al., 2018), and retail work systems (Van de Weerd et al., 2019).

4.2.3.2 Data Gathering

The data collection period for this study is June to August 2021. This study conducts online semi-structured interviews lasting between 45 and 60 minutes in the Javanese and Indonesian languages. Later, this study transcribes the text into English. Each interview adheres to predetermined interview guidelines: it focuses on operational employees who execute processes daily and know workarounds. It also conducts document analysis where documents are made available. However, it does not undertake in-person, on-site observation (due to COVID-19 restrictions).

The unit of observation is an organisational process, and the unit of analysis is a workaround. The study recruited 12 respondents with 776 minutes of interview data (see Table 4.6). Each respondent was an operational employee in the data broker. This study defines a data broker as a unit (both formal and informal) that collects, transforms, and analyses data obtained from other units and reports the results to stakeholders. It addresses various stakeholders' needs (e.g., reporting type and time). It sets local policies and standards for data collection and maintains the infrastructure. In an organisation where data are collected, a data broker is required. It characterises data brokers in the three field sites: the plantation company (formal), the university (formal), and the government agency (informal). In the formal data broker, all unit members are permanent members.

Also, the organisation formally established the unit for managing data across units (only). In the informal data broker, all unit members are temporary, and so is the data broker unit. It can be disposed of at any time. As a data broker employs a few employees, the respondent size was small, see Table 4.6.

Table 4.6 Respondent Information

No	Field Study	Number of respondents	% of employees (data broker)	Institution
1	Plantation Company	6 respondents	85%	QA unit (head office)
2	Government Agency	3 respondents	100%	Government bureau
3	University	3respondents	75%	Academic office

For each interview, this study asks 1) How do you work? 2) What data do you need in your work? 3) What tools do you use to handle data in your work (e.g., software, hardware, cloud, paper)? These questions allowed each interviewee to present their experience executing the process and the WCDA. The following sub-sections present each site as well as its internal processes.

4.2.3.3 The Plantation Company

The plantation company is a state-owned company focusing on producing sugar. The company was established in 1996 as a combination of several sugar factories. It employs around 14,083 employees (2018). Now, the company manages nine major sugar factories in the East Java Province of Indonesia. It collects data from the QA unit that serves as a "data centre" for the company. As a data broker, it must provide daily sugar production reports for all stakeholders, including the board of directors and regulators. It must provide early warning systems if the organisation fails to achieve specific working parameters for sugar production. These parameters include sugarcane plantation qualities, soil quality, rainfall rate, pests and weeds, and reactor acidity and temperature.

The plantation company utilises two disconnected centralised systems: SAP ERP and e-Farming, and countless disconnected systems (e.g., spreadsheets). As a result, some necessary data are unavailable when required. The QA unit collects work progress reports (as formatted spreadsheets) from

sugar factories to solve this problem (as a workaround). Each sugar factory must submit this report daily before 10 am. The QA unit can analyse the data before entering it into SAP and producing the required reports. The employees' use of spreadsheets is problematic, and mistakes can happen (e.g., inputting extra zeros or putting data in the wrong cells). So, data accuracy issues materialise for the QA unit.

4.2.3.4 The Government Agency

The government agency is a provincial government entity in Indonesia. It has the most significant local governments in Indonesia (29 regencies and 9 municipalities). Along with these local governments, the agency also administers 12 regional technical institutions and 5 regional hospitals. Given this large number of local units, the agency employs a small team in the government bureau. The team is responsible for periodically collecting data for annual reporting. This team acts as a data broker that mediates between multiple data consumers (e.g., ministries, house of representatives) and data providers (e.g., local units).

As a data broker, this small team must face the reality that each local unit has disconnected systems supporting its operations. These systems range from spreadsheets, and cloud systems, to complex information systems. So, data integration is a constant challenge. To alleviate this challenge, the small team "creatively" introduced another web-based application to collect data (viewed as a workaround). Each local unit must enter data into the new system regularly. It also means that the new system imposes an extra burden on employees. For example, a local unit employee can enter the same data three times in three separate applications. Hence, some employees are reluctant to enter high-quality data when needed. Therefore, data accuracy issues materialise for the government bureau.

4.2.3.5 The University

The university is a public university and is the second-largest engineering school in Indonesia. It was established in 1957 in Surabaya. It has around 17,625 students annually, with 1,018 faculty members (2016).

Currently, it has nine faculties with 92 departments. This study focuses on the academic office. This unit acts as a data broker because it retrieves data from various sources to release graduate certificates and transcripts. Even though the process appears simple, it is not. The centralised system does not provide specific data, such as the most recent student photo. So, the data must be collected manually from around 4,500 students annually. As a workaround, the unit provides a Google Form to collect the data directly from the students.

Interestingly, some students upload the wrong data (e.g., incorrect photos) because the required data seems unimportant. So, data accuracy issues materialise. They introduce manual processes of checking the accuracy of the data due to many students. These processes are resource-demanding and time-consuming. Moreover, as part of the analysis, this research uses a NN approach to model these WCDA. These rules and the analysis are presented in the following two sections.

4.2.3.6 NN Approach to model WCDA

This study applies WCDA modelling rules (Wibisono, Sammon, & Heavin, 2022c) to model *patterns of action* across the three sites. Table 4.7 shows how it establishes a NN and applies WCDA modelling rules. Establishing a NN requires four steps: 1) Choose a process and define its boundaries, 2) Adopt a point of view, 3) Collect the narratives and code the fragment, and 4) Relate a code with sequences.

Following the first step, this research designates that each *workaround* must satisfy a particular purpose: dealing with data accuracy issues. The second step suggests that a narrative fragment must come from a process actor. So, it ensures that the respondents are operational people dealing with day-to-day variabilities. Also, it assures that they are active members of the three *data brokers:* the QA unit, government bureau, and academic office. In the third step, there are four rules.

Table 4.7 Step-by-step to establish the NN.

No	Step	Explanation	The **application**
1	Choose a process and define its boundary	Focus on "purpose."	Purpose: This study examines a workaround to manage data accuracy issues.
2	Adopt a point of view	Rule 1. A narrative fragment must come from a process actor	Process actors were operational employees in the QA unit (plantation company), government bureau (a government agency), and academic office (university). It ensures that these employees are operational staff that are executing workarounds.
3	Collect the narratives and code the fragment	Rule 2. A narrative fragment has three attributes: actor, action & resource	It interviews process actors. It transforms the interview texts into text. It extracts narrative fragments from the texts. In doing so, it applies a subject-verb-object structure. An example of how this study applies this structure is in Table 4.8
		Rule 3. All attributes in a narrative fragment establish the action type	It examines three attributes in Rule 2 to verify whether a narrative fragment is a workaround.
		Rule 4. A narrative fragment must contain a data activity	It models data activity (e.g., transfer data, evaluate data, correct data)

		Rule 5. A narrative fragment data activity must follow a standard naming convention	Here, to generalise, it employs open coding. Consequently, it can standardise action labels for all narrative fragments.
4	Relate code with sequences	Visualise the NN – to establish a pattern of action	It connects all data activities. Thus, it can construct a pattern of action.

As to Rule 2, in establishing the narrative fragments, this study focuses on three things (actor, action, resource) and how they relate. Rule 3 determines whether a narrative fragment is a workaround and assesses all attributes: actor, action & resource.

Regarding Rule 4, it only extracts data activities from the narratives. Therefore, it excludes any activity that is not a workaround or a data activity. As to Rule 5, it applies open coding to standardise action (data activity) naming. Consequently, it can better analyse the NN. Step 4 visualises the NN by connecting all data activities (see Table 4.7).

4.2.3.7 Data Analysis

This study uses open coding (Corbin & Strauss, 1990) to analyse interview texts from all respondents (see Table 4.8). After that, it translates this coding into a narrative network (visual) to represent the WCDA linked with addressing data accuracy issues (see Figure 4.4, Figure 4.5, Figure 4.6). Here, open coding provides a convenient way to generalise the label of three components in each narrative fragment: actor, action, and resource. So, it can establish a shared naming standard across the three field studies (based on grounded data). This grounded approach identifies and classifies real-world events. Also, this approach reduces cognitive overload in continuous cycles of analysis while maintaining the validity of the work. Thus, it facilitates theorising. There are several findings from the open coding.

First, this study finds two types of actors dealing with data accuracy issues: brokers and providers. A data broker is a unit that does data brokering functions in an organisation: collecting data, analysing data, transferring data, and reporting data. A data broker serves multiple stakeholders for detailed data (e.g., reporting): internal managers, board members, regulators, and domain communities. So, a data broker acts as a data mediator between data providers and data consumers. A data broker collects the data from multiple data providers. A data provider is any party that owns the data – even though it may not be the data producer. A data provider can be an individual (e.g., a university student) or an employee in a particular unit (e.g., a sugar factory employee).

Table 4.8 Text Excerpts for Plantation Company

No	Sample extracts from interviews	Actor			Action			Resource		
		1st Order	2nd Order	3rd Order	1st Order	2nd Order	3rd Order	1st Order	2nd Order	3rd Order
1	Yes, the sugar factory sent data to us by email.	Sugar Factory	Sugar Factory Employee	Data Provider Employee	Sent	Transfer	Transfer	It	(*Data*) Production (*Artefact*) Email	(*Data)* Data (*Artefact)* Email
2	Later, Mr John has given weight to the report.	John	QA Unit Employee	Data Broker Employee	Give weight	Assess	Evaluate	Report	(*Data*) Production	(*Data)* Data
3	The friend prints out the reports	The friend	QA Unit Employee	Data Broker Employee	Print	Transfer	Transfer	Report	(*Data*) Production	(*Data)* Data
4	We check (the field). Is it true that the report is correct?	We	QA Unit Employee	Data Broker Employee	Check	Retrieve	Retrieve	The field	(*Data*) Production	(*Data)* Data
5	Next, we calculate the deviation.	We	QA Unit Employee	Data Broker Employee	Calculate	Evaluate	Evaluate	Deviation	(*Data*) Production	(*Data)* Data
6	If the difference is too high, we suggest checking the sugar factory.	We	QA Unit Employee	Data Broker Employee	Check	Evaluate	Evaluate	The difference	(*Data*) Production	(*Data)* Data

Later, a data provider must supply the intended data to the data broker for reporting. Furthermore, it finds that a data broker coordinates multiple data providers.

Second, the open coding reveals six data activities that address data accuracy issues. These data activities are: retrieve data, transfer data, evaluate data, correct data, validate data, and request for action (see Figure 4.4, Figure 4.5, Figure 4.6).

Retrieve data is an activity in which an employee gathers data from intended sources such as data providers or fields. Employees only retrieve the data with data accuracy issues. So, the data are individually collected from the source, not in a batch.

Transfer data is *an* activity to transmit data to other employees (e.g., data provider or data broker) or devices (e.g., paper, USB stick). In transferring data, the data content remains unchanged.

Evaluate data is an activity to identify the root of data accuracy issues and formulate a solution. It encompasses some data activities such as checking and calculating. It is essential because it determines how to solve data accuracy issues.

Correct data is an activity to alter the data for better accuracy. This activity is an invasive activity to improve data quality. Correct data can be done on independent files (e.g., spreadsheets, paper-based files, documents) or in the centralised system.

Validate data is an activity to verify that the data correction is complete. Once complete, the data provider cannot alter the data. This data activity is vital to track changes in the corrected data.

Consequently, the credibility of the corrected data can be assured. The final data activity is a *Request for Action*. This data activity facilitates either data providers or data brokers asking another party to do something. For example, a data broker can ask a provider to correct or transfer data. This data activity is essential because it enables critical coordination between data brokers and data providers. The following section presents the analysis and discussions from the observations.

4.2.4 Findings and Discussion

This section discusses the findings. It describes three emerging patterns of action from the field studies: field inspection – plantation company; fast authorisation – government agency; gold standard making – university.

4.2.4.1 Pattern #1: Field Inspection

This pattern is observed in the plantation company (see Figure 4.4). It reflects how employees address the data accuracy issue. The story begins when the plantation company prepares for sugarcane milling by checking various parameters in each sugar factory to avoid production failures. As the data are unavailable in SAP, the QA unit receives work progress reports (as a spreadsheet). Therefore, the use of spreadsheets is a workaround. Based on these reports, the QA unit assembles teams to visit each sugar factory. In the meantime, once the reports are received, a QA unit employee prints these reports on physical paper. Next, each QA unit employee is allocated to a particular sugar factory. A QA unit employee can visit three to five sugar factories to check the data.

At this point, the *Field Inspection* pattern begins. In this pattern, an employee retrieves data from the sugar factory. Next, the employee calculates the deviation between the reported data and their observations. The sugar factory employee must correct the data if the deviation is significant.

On the one hand, visiting sites can be time and resource-consuming for travelling. Therefore, the organisation must anticipate unexpected costs, emergencies, and cultural shocks during visitation. Further, it requires employees' knowledge and experience to search, scan, and notice discrepant cues in the field related to the data. Otherwise, the employee can struggle to interpret current situations, resulting in further data accuracy issues.

On the other hand, this pattern allows data broker employees to capture data directly from the source (point of data creation). It reduces the bias produced by inexperienced data producers or data providers. Additionally, it allows data broker employees to meet their data provider colleagues. So, this pattern can facilitate a better sense of belonging and improve data-related coordination. Furthermore, the request for action in the pattern enables the data

provider employees to reflect on the data. It identifies what process fragilities trigger data accuracy issues and how to resolve them. Consequently, employees can formulate a strategy to avoid similar data accuracy issues emerging in the future.

4.2.4.2 Pattern #2: Fast Authorisation

This pattern is observed in the government agency (see Figure 4.5). It reflects how employees address the data accuracy issue. Initially, data broker employees identify errors in the submitted data. However, data provider employees do not respond well to correcting the data. As a result, data broker employees continuously issue a "request for action" to submit corrected data. Fatigued by the constant requests, the employees eventually submit the data. As such, employees enter corrected data in the designated system but do not validate it. Otherwise, these employees submit corrected data elsewhere (e.g., via WhatsApp). So, the organisation never properly corrects and validates the data in the designated system.

At this point, the *Fast Authorisation* pattern begins. To start with, the employee checks whether the data are correct. Later, a data broker employee corrects and validates the data: as a proxy to save time. It is because data provider employees demonstrate slowness in revising data in the designated system. This slowness can hinder the timeliness of report production.

On the one hand, this pattern does not solve data accuracy issues at the source. Therefore, the employee of the data provider can repeat an unacceptable work ethic (e.g., late correcting of data). This repetition over time equates to the existence of a *Hidden Data Factory* (Redman, 2016b). Moreover, as the data broker employee, not the data provider, validates the data, data provider employees can always revise the data. So, the data can be unstable in supporting future decision-making, reducing trust and faith in the data. Evaluating data on the data broker side requires knowledge of and skills around the data. Data accuracy issues can persist if the data broker employee lacks expertise. Also, this pattern imposes more burden on the data broker.

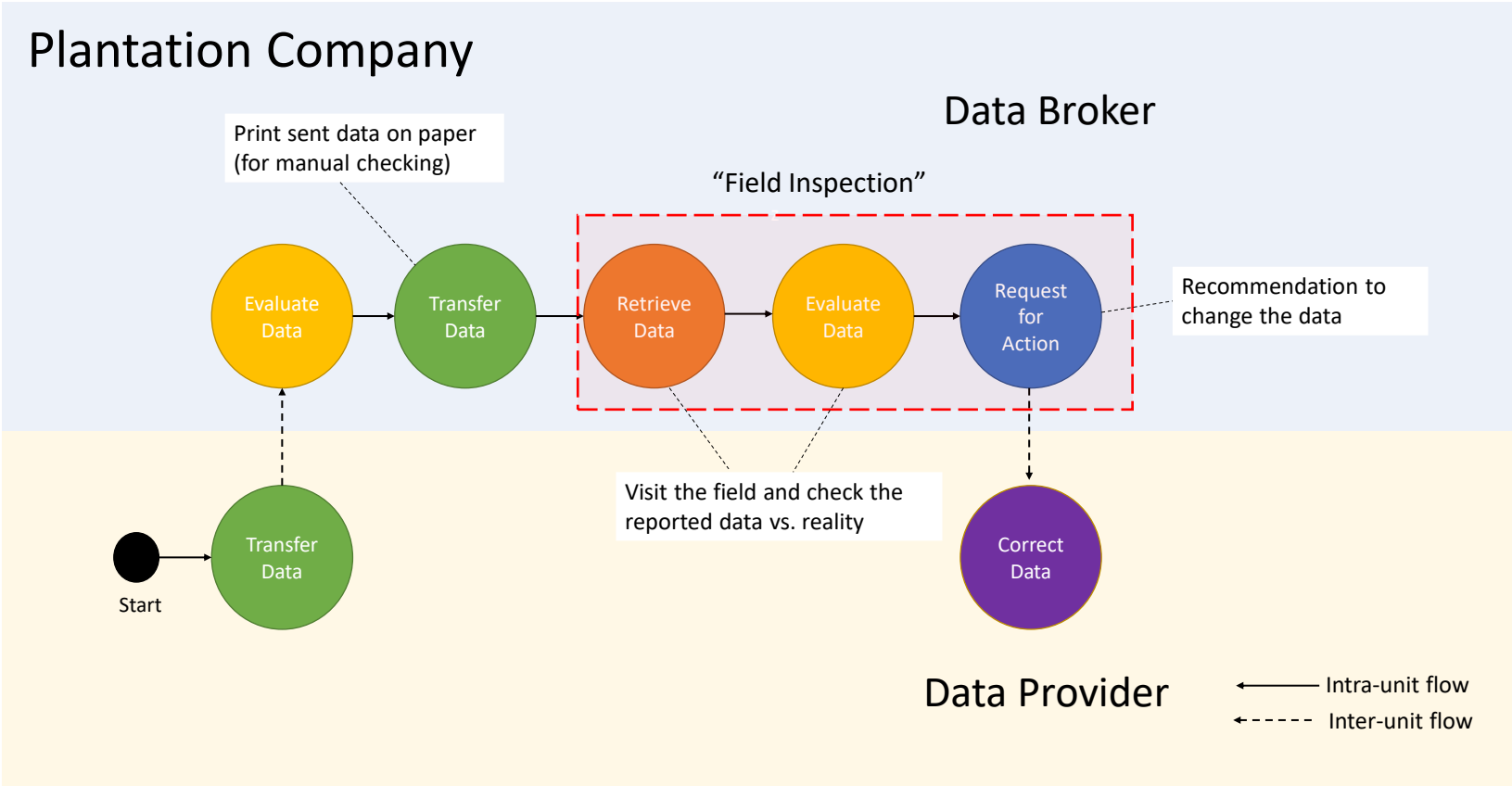

Figure 4.4 Narrative Network of the Plantation Company

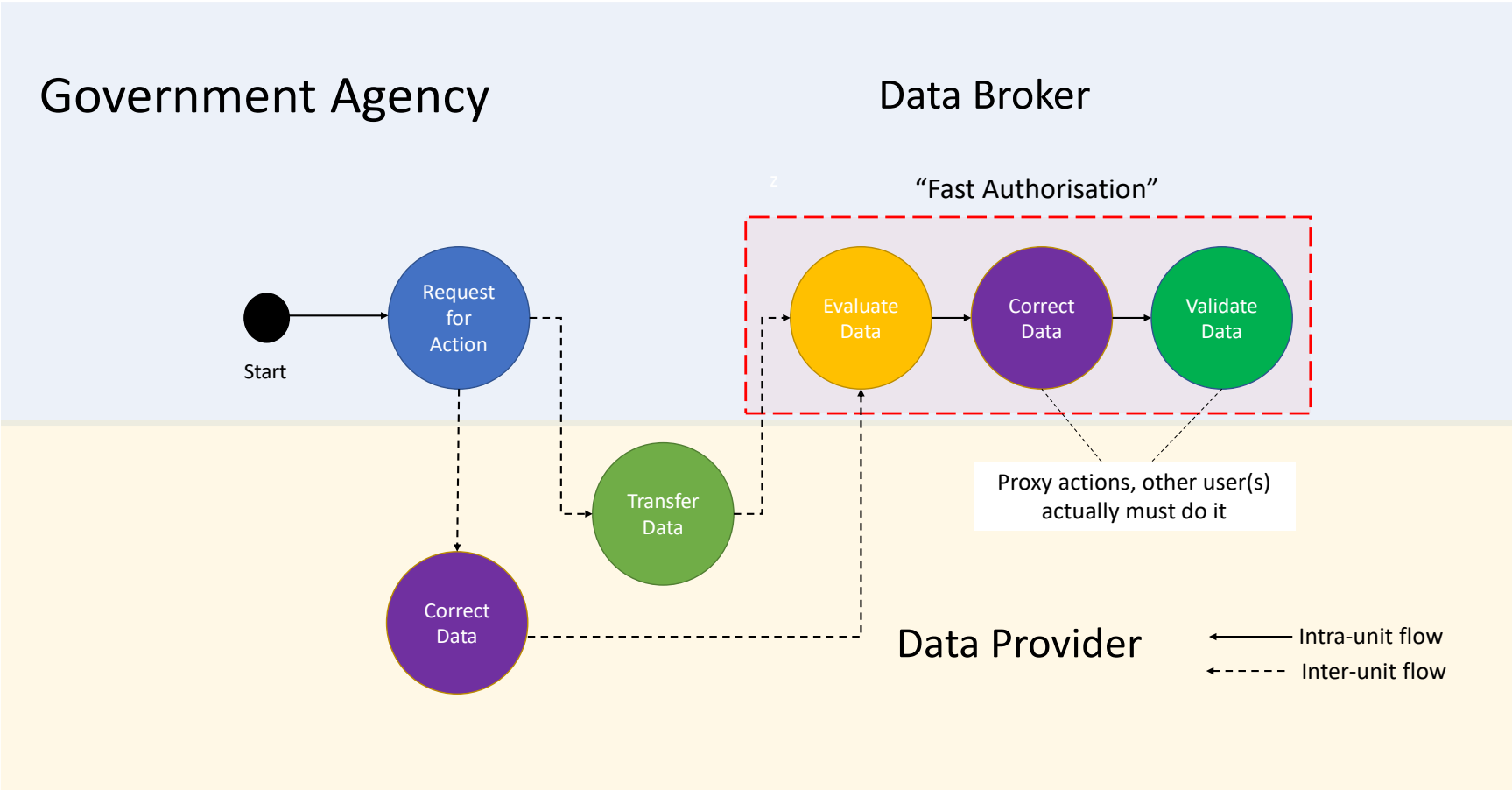

Figure 4.5 Narrative Network of the Government Agency.

Data broker employees can be responsible for any data error in the data customer's eyes. So, it potentially introduces burnout for data broker employees. Primarily to address constant data customers' needs and collect data from data providers.

On the other hand, this pattern allows the organisation to respond faster to data accuracy issues. Therefore, it is suitable for demanding data customers. Also, it reduces the technology gap among the data provider employees. These employees do not need to learn new technology. Instead, they only need to use their spreadsheet knowledge and skills to manage data. Hence, they produce higher working satisfaction for data provider employees. Thus, it makes continuous data collection possible and sustainable.

4.2.4.3 Pattern #3: Gold Standard Making

This pattern is observed in the university (see Figure 4.6). It reflects how employees address the data accuracy issue. The process story begins when students finish uploading data for processing at graduation (e.g., student id, name, address, birthplace, birth date, birth certificate, highest diploma certificate, photos) and validate these data (in the Google Form). At this point, the *Gold Standard Making* pattern begins (once most all students complete the uploading of data for graduation).

Initially, the employee prints all documents from the Google Form on physical paper. After that, the employee (as data broker) evaluates the submitted data with the documents generated from the centralised system to find data accuracy issues. As such, the accuracy is measured by the consistency of the data across the collection of student documents. Suppose employees find data issues in a document (e.g., name, date of birth, place of birth). In that case, they can check other data sources (e.g., highest diploma certificate, birth certificate).

On the one hand, this process is laborious because employees check more than 2,500 students at each graduation. If they can find solutions to data accuracy issues, the employees correct the data immediately. Otherwise, they ask each student (as data provider) for a solution (e.g., which data are correct).

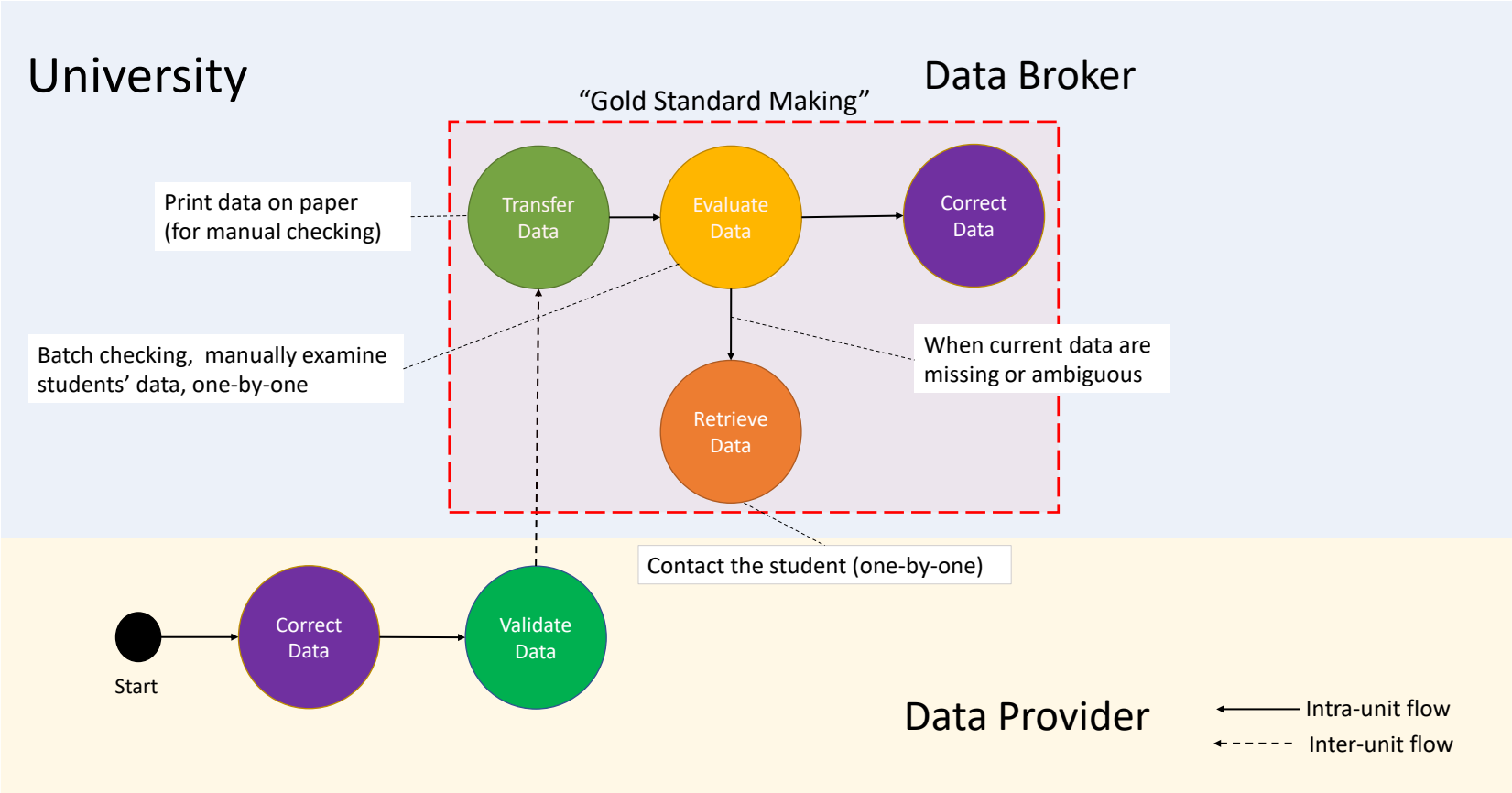

Figure 4.6 Narrative Network of the University

On the other hand, this pattern is quick as it reduces the interaction with data providers (e.g., students). The interaction only occurs when the employees cannot solve the problem. Therefore, the process becomes more efficient. Moreover, this pattern allows the academic office to complete these tedious data tasks in (only) a few weeks. This strategy allows them to avoid constant switching between printing certificates and other academic-related data tasks ("large volumes, once" versus "small volumes, frequently").

Furthermore, employees executing this pattern in a batch allows for a good audit trail. All events (e.g., evaluate, correct, retrieve data) happen (almost) simultaneously. It provides enough opportunity for communal reflection about what is happening with the academic data (e.g., problems and their solutions). This reflection can help a transparent audit trail of data when documented.

4.2.4.4 Kekeluargaan in Field Inspection Pattern

The plantation company's effort to address data accuracy issues is defined by what this study calls the *Field Inspection* pattern. QA unit employees can visit the site and collect sample data. Once collected, sugar factory employees evaluate the data. The reported data may be incorrect. In this situation, the QA unit employee becomes a "father" to the sugar factory members (see this as ***Bapakism***): managers, assistant managers, and junior assistant managers. As such, data abnormalities can affect the whole company as a family. So, the QA unit employee does not hesitate to rebuke, even though managers are senior in the organisational hierarchy.

As a QA unit employee reveals: "*so when we supervise, if we find something like that, we provide insights (to them). I do not care if it's the assistant manager, his young assistant, or even the manager himself. We give insights to all. When giving numbers like this, what are the risks? If you give the numbers as they are, how will they benefit? We often do that. So, when there is a problem (with data), they can have difficulty finding the error by giving a "good" number. But if the correct number is given, the abnormalities can be easier to find*". Consequently, the QA unit employee (as *Bapak*) can evaluate

data and nurture an "honest" culture in the company. So, it can prevent data accuracy issues from materialising.

The exciting point about the *Field Inspection* pattern is that *Bapak* does not force his view on the data after inspection. An employee mentions: "When we supervise anything that we (should) check. We give a value. We evaluate. What are the shortcomings or *the issues, then we can give recommendations*". This behaviour shows tolerance and an attempt to accommodate all views (Hermawan & Loo, 2019), so this study observes **Musyawarah Mufakat** in this pattern.

4.2.5 Kekeluargaan in Fast Authorisation Pattern

The *Fast Authorisation* pattern is one in which correcting and validating data are completed once, proxied by an employee in the government bureau. This pattern addresses a situation where few capable employees in the local unit can complete the tasks. As a result, correcting and validating data are delayed or not performed. As one employee puts it: "*Sometimes there is also a shift of tasks. The officer (finally) can't enter (the application). So, we sometimes understand that too. (We know that) there are currently many shortages of human resources*". So, ***Gotong Royong*** informs the *Fast Authorisation* pattern (Hermawan & Loo, 2019, p. 2). It reflects the willingness to provide mutual assistance and share burdens (Mulder, 2005).

Similarly, ***Rukun*** drives this pattern, where avoiding potential conflict is essential (Magnis-Suseno, 1984). By proxying, the government bureau employee does not force the data provider employees to enter the data, thereby avoiding potential conflict.

4.2.5.1 Kekeluargaan in Gold Standard Making Pattern

In the *Gold Standard Making* pattern, employees in the academic office team up to manually check each student's data. The process uses physical paper and is manually intensive. Thus, the process is very time-consuming and resource-demanding. It can take more than one week, and sometimes, it requires the help of seasonal employees. Even though this process is complex, it has existed since 2006.

As such, ***Gotong Royong*** is responsible for this pattern. As a family, employees believe that they act as "parents" and that these students are their "children" and must share the burden. So, as the university releases the graduate certificate only once, the data on the graduate certificate must be correct. Otherwise, students can have difficulty entering the job market. For example, the Indonesian government uses graduate certificate data (not birth certificates, ID cards, or passports) to appoint applicants to public office. Issues with data accuracy can affect many things (e.g., pension and health insurance). Changing the ID card's data are more accessible than changing the graduate certificate data. As one employee mentions: "*because the guidelines are like this, (in fact) changing ID cards is easier than changing the graduate certificate*". These employees spend much time and effort ensuring that the issue with data accuracy does not occur.

Similarly, **Musyawarah Mufakat** is also responsible for this pattern. For example, when data contradictions are identified (e.g., higher diploma vs birth certificate), the employee asks the student to confirm the correct data. The employee can give what-if suggestions to the student: "*we contact the students. We told them there was a difference between the ID card and the last diploma. So, we (ask) them to see the history. How about starting from an elementary school diploma to the last one? Well, where are the mistakes*?"

4.2.5.2 Kekeluargaan in Addressing Data Accuracy

Overall, these three patterns represent three strategies to address data accuracy issues. This study considers these strategies: *invasive*, *permissive*, and *anticipative* (see Table 4.9).

First, *invasive* means that data broker employees "invade" data provider "territory" by sampling data in the field. As such, power through *Bapakism* is needed to gain access and force a certain work ethic in dealing with data. However, this power should not be used to manipulate data. Otherwise, the data accuracy issues persist. Therefore, *Musyawarah Mufakat* is needed to reflect on what is going on.

Second, *anticipative* means that even though the data broker employees have the data, they anticipate that some data are wrong. So, they check them

one by one. It reflects Gotong Royong because the tedious tasks are distributed equally to all employees. It also reflects *Musyawarah Mufakat* because it allows data providers to appreciate their problems with data accuracy and its potential solution. By having these two materialise, the data provider can transfer some risks to the data provider related to altering data (e.g., incorrect data).

Third, *permissive* means that data broker employees allow data provider employees to execute the "half" of the process. Here, data broker employees can complete the other "half". *Rukun* underpins this strategy as it avoids further conflict by continually asking to enter data. *Gotong Royong* also underpins this strategy by sharing the burden of data providers. Both *Rukun* and *Gotong Royong* are essential to promoting data providers' satisfaction. These values are essential to keep everything working over a sustained period, mainly when the data producer differs from the data provider.

4.2.6 Conclusion

This research examines WCDA *patterns of action* to address data accuracy issues. So, to fulfil the objective, this study conducts three field studies in Indonesia: a plantation company, a government agency, and a university. It finds that issues with data accuracy generates three patterns of action: *Field Inspection*, *Fast Authorisation*, and *Gold Standard Making*. It outlines the advantages and disadvantages of each pattern for data governance, and it explains how the Javanese value of *kekeluargaan* shapes these patterns.

4.2.6.1 Theoretical Contributions

The theoretical contributions to workaround research are twofold.

First, this research challenges the traditional way of thinking in workaround research, which assumes that a workaround is a monolithic and atomic process (cf. Koppel et al., 2008; Vogelsmeier et al., 2008). This research opens the workaround black box. Showing data activities and their relations. As theoretical implications, this understanding supports further identifying non-data activities in a workaround. So, it helps to understand why two seemingly similar workarounds can impose different consequences on an organisation.

Second, it advances the understanding of WCDA and their relationships (as patterns of action) to address data accuracy issues. It finds six data activities used to overcome data accuracy issues: *correct* data, *evaluate* data, *transfer* data, *retrieve* data, *request for action*, and *validate* data. These six activities are linked to each other and establish three patterns of action: *Field Inspection*, *Fast Authorisation*, and *Gold Standard Making*.

These contributions are insightful as it has introduced something new that changes the way of thinking (Leidner, 2020) in workaround research. As it is the first in elaborating WCDA to address data accuracy issues, it brings something *novel* to work around research. Research suggests *insightfulness* (Leidner, 2020; Sparrowe & Mayer, 2011) and *novelty* (Cornelissen, 2017; Leidner, 2020; Mueller & Urbach, 2013; Sparrowe & Mayer, 2011) are pivotal. They are pivotal for acceptable theoretical contributions (Leidner, 2020).

4.2.6.2 Managerial Implications

Theoretical insights demonstrate that data accuracy is not a given and is difficult for managers and system designers to comprehend *completely*. Therefore, improving data accuracy demands thoughtful practices. It necessitates a thorough development of the data. Also, it necessitates intensive system design knowledge and ongoing supervision (for all data aspects). Additionally, faults that cause or spread difficulties with data accuracy must be fixed continuously. So, this study suggests several recommendations for data provocateurs in an organisation.

First, data provocateurs need to automate routine, repetitive day-to-day organisational processes. They can automate the process using industrial-driven technologies such as Robotic Process Automation (RPA) or Business Process Management Systems (BPMS). Hence, an organisation can improve productivity, reduce costs, minimise data errors, and save each employee's time.

Second, data provocateurs should remove human actors from capturing data associated with automatic or non-automatic processes. They can use IoT, sensors, and artificial intelligence to gather data automatically without human

input. Consequently, this research can improve data accuracy by eliminating human errors in capturing data.

Third, consider a situation where removing human actors is impossible. Here data provocateurs need to train other employees with sufficient domain-driven knowledge and skills. Each employee can enter data correctly in the designated system. So, this understanding can help employees assess the impact of producing inaccurate data.

Fourth, suppose many data originate from other sources disconnected from internal information systems. In that case, data provocateurs must develop software intermediaries to capture data automatically. For example, they can develop an Application Programming Interface (API) to link one application to many applications. So, the data can be obtained when needed without human intervention.

If data accuracy issues materialise, some values can solve the issues.

First, bapakism is related to power, suitable for invasive strategies such as field inspection patterns. Suppose one executes it in the right direction. In that case, it can enhance an organisation's data culture. This data culture encompasses low data discipline to enter data, laziness in collecting data, and sectorial egos among data providers. Otherwise, if one executes it incorrectly, it can retain the organisation's status quo. It is leading to sustainable data accuracy issues (see Table 4.9).

Second, *rukun* prepares each provocateur's "internal feeling" with the various possibilities with data. So, *rukun* is appropriate for situations where multiple powers exist in correcting data. One can see this as an individual-centric "risk acceptance mechanism. Also, *rukun* produces self-mindfulness about data-related knowledge. So, none can push their views on how to correct the data. This situation can facilitate the emergence of good data quality. Organisations can exploit *rukun* for *permissive* or *anticipative* strategies (see Table 4.9).

Table 4.9 Data Accuracy Issues and Solutions

No	Data Accuracy Issues	Approach to Addressing Data Accuracy Issues							
		Strategy	Pattern of Action	Bapakism	Rukun	Musyawarah	Mufakat	Gotong	Royong
1	A primary data source is unknown	Invasive	Field Inspection	✓		✓			
2	Data duplication across voluminous data sources	Anticipative	Gold Standard Making			✓		✓	
3	The data provider refuses to provide access to the primary data source	Invasive	Field Inspection	✓		✓			
4	Poor discipline in entering correct data	Invasive	Field Inspection	✓					
5	Data providers cannot correct data	Permissive	Fast Authorisation		✓			✓	

Third, as *gotong royong* is related to collective work, it is necessary to handle high data volume. It distributes the work to all organisation members as data provocateurs and offers assurances that they work. It also can mobilise new "workers" from different "families" to join in handling the data (whenever needed). This value is good for anticipative (e.g., gold standard making) strategies (see Table 4.9).

Fourth, *musyawarah mufakat* accommodates various views and knowledge about data content. Hence, it produces a reasonable consensus for data correction. It shares the responsibility for data correction across multiple data provocateurs. Hence, it increases data accountability and data sharing across units. This value is good for invasive strategies (see Table 4.9).

4.2.6.3 Limitation and Further Research

There are several limitations of the work. First, this study captures data from data broker employees (not data provider employees). So, it blacks box any process to correct data in data providers. It focuses only on data brokers. As a result, it may not capture the complete complexity of correcting data. However, as it focuses (only) on data brokers, it can prevent complex patterns of action from emerging, which are difficult to analyse and theorise.

Second, data accuracy issues cause three WCDA *patterns of action* to materialise. However, it cannot thoroughly explain the underlying mechanisms that trigger these patterns. These underlying mechanisms are partially tacit, distributed among participants, and sometimes embedded in the technology used (Pentland et al., 2010). Therefore, future research can investigate how these mechanisms are organised temporally and spatially.

Third, each pattern of action is part of an ongoing process to fix data. However, many data activities belong to data providers. How the ongoing process finally concludes remains unclear. For example, data providers can mindlessly execute the final data activities, producing another workaround cycle.

So, this research opens some research opportunities.

First, future research can investigate the mechanism of each pattern to influence several data governance indicators. For example, how does the

pattern minimise data-related costs and risks? How does it address data privacy, accessibility, compliance, security, and ownership issues? How does it increase the value of data for the organisation? Hence, organisations can formulate improved data governance policies for workarounds and data accuracy issues.

Second, future research can examine different patterns of action triggered by other data issues. For example, data availability, data completeness, credibility, access, presentation, duplication, format, volume, and privacy. What are the shared patterns of action that these data issues produce? What patterns of action are specific to data issues? This understanding facilitates the development of a "pattern" taxonomy to deal with data issues. This taxonomy must be able to classify data-related organisations. So, it acts as a parsimonious framework to describe complex organisational forms for data governance.

Third, future research can examine other Javanese values such as *tepo seliro* (toleration), *isin* (shyness), and *sungkan* (hesitations). These values may positively alleviate various data issues such as availability, credibility, protection, and security.

Overall, data accuracy issues are challenging for organisations to identify and solve. So, the best way to deal with these issues is (actually) to prevent them from occurring. Thus, organisations can prevent WCDA and their patterns of action from manifesting as hidden data factories.

4.2.7 Appendix

Table 4.10 Text Excerpts for Government Agency

No	Sample extracts from interviews	Actor			Action			Resource		
		1st Order	2nd Order	3rd Order	1st Order	2nd Order	3rd Order	1st Order	2nd Order	3rd Order
1	Sometimes we chat via WhatsApp to update	We	Government Bureau Employee	Data Broker Employee	Chat to update	Request for Action	Request for Action	WhatsApp	(Artefact) WhatsApp	(Artefact) WhatsApp
2	(Finally) it's been updated (by the unit), but the status hasn't changed	Unit	Government Unit Employee	Data Provider Employee	Update	Correct	Correct	It	Indicators data	(*Data*) Data

3	Or sometimes, the file is also sent (by the unit) via WhatsApp	Unit	Government Unit Employee	Data Provider Employee	Send	Transfer	Transfer	The file	Indicator data, WhatsApp	(*Data*) Data (*Artefact*) WhatsApp
4	**we** cross-check. Is this proper or not?	We	Government Bureau Employee	Data Broker Employee	Cross check	Evaluate	Evaluate	This	Indicator data	(*Data*) Data
5	But sometimes, due to the busyness of the Head/sub-section or their ignorance, I <u>change</u> it.	I	Government bureau Employee	Data Broker Employee	Change	Correct	Correct	It	Indicator data	(*Data*) Data
6	Then I <u>validate</u>. Everything.	I	Government Berea Employee	Data Broker Employee	Change	Correct	Correct	Everything	Indicator data	(*Data*) Data

Table A. 1 Text Excerpts for University

No	Sample extracts from interviews	Actor			Action			Resource		
		1st Order	2nd Order	3rd Order	1st Order	2nd Order	3rd Order	1st Order	2nd Order	3rd Order
1	I used the Google Form to give them a chance to correct the NIK (national identification number).	Them	The student	Data Provider Employee	Correct	Correct	Correct	NIK, Google Form	Academic Data, Google Form	(*Data)* Data (*Artefact)* Google Form
2	Now, the data given is declared 'true' (by the student), I am responsible and so on. Like a disclaimer	The student	The student	Data Provider Employee	Declare	Validate	Validate	Data	Academic Data	(*Data)* Data
3	So, in that Google Form, there was a print preview. So, the print preview (data) is printed, then matched (by me)	Me	Academic Office Employee	Data Broker Employee	Print	Transfer	Transfer	Data	Academic Data	(*Data)* Data

4	So, in that Google Form, there was a print preview. So, the print preview (data) is printed, then matched (by me)	Me	Academic Office Employee	Data Broker Employee	Match	Compare	Evaluate	Data	Academic Data	(*Data)* Data
5	So, if there is a mistake, we will correct it	We	Academic Office Employee	Data Broker Employee	Correct	Correct	Correct	It	Academic Data	(*Data)* Data
6	We will contact the student if there is a case (with the data).	We	Academic Office Employee	Data Broker Employee	Contact	Retrieve	Retrieve	Data	Academic Data	(*Data)* Data

4.3 *Paper* 6: Theorising approaches to identify data issues.

4.3.1 Introduction

Data issues can affect organisational strategies to operational decisions (Nagle et al., 2020). Issues with data quality can impact customer satisfaction and job satisfaction, increase operational costs, hurt employee morale, and breed organisational mistrust (Haug et al., 2011; Redman, 1998). Research shows that the total cost of data issues in the US is at least $1.5 trillion annually (Fisher, 2009). This number can amount to 8–12% of revenue (Redman, 1998). Data issues are difficult to estimate (Redman, 1998), so the total tangible and intangible costs can be even higher.

Data quality research discusses various methodologies to address data issues (Batini et al., 2009; Nagle et al., 2020; Pipino et al., 2002; Sebastian-Coleman, 2013). However, mainstream research assumes that addressing data issues is *preventive*. Hence, it is pre-determined and top-down. For example, Batini *et al*. (2009) suggest two strategies for avoiding data issues: a *data-driven strategy* (e.g., acquisition of new data, record linkage, data, and schema integration) and a *process-driven strategy* (e.g., process control, process redesign). Pipino *et al.* (2002) suggest three sets of steps to avoid data issues: 1) performing subjective and objective data quality assessments; 2) comparing the results of the assessments, identifying discrepancies, and determining root causes of discrepancies; and 3) determining and taking necessary actions for improvement.

Preventive assumptions can help formulate a comprehensive approach to data quality. However, they require a lengthy deployment time, careful monitoring, and post-deployment control. Infrastructure issues (Born & Krönung, 2016), lack of skilled people (Steinhueser et al., 2017), poor software functionality (Davison et al., 2019; Ibrahim et al., 2019), and poor software usability (Jagannath et al., 2019; van den Hooff & Hafkamp, 2017) can present challenges for an organisation. Because of these obstacles, employees can

mindlessly produce incorrect or incomplete data to "finish" their work tasks sooner. Therefore, to obtain "quality data", other employees must identify and correct these data issues (Wibisono, Sammon, & Heavin, 2022a). Therefore, the reality of addressing data issues is (actually) more *curative* (e.g., *after* the data are produced). It is *preventive* for organisations (e.g., *before* the data are produced) (cf. Wibisono, Sammon, & Heavin, 2022a).

Therefore, organisations employ data brokers to *deliver "quality data" to meet pressing needs curatively*. They identify data issues earlier and "solve them" before data consumers use them. So, understanding how data broker employees work is essential to address data issues. Given these facts, this research poses the following question:

RQ. How do data broker employees identify data issues?

This study makes three significant contributions to data quality research. First, it challenges the assumption in data quality research that addressing data issues must be a *preventive* process. It shows that the process can be *curative* as well. Second, it examines how data broker employees identify data issues. It shows approaches that data broker employees use to recognise data issues. Third, it shows how these approaches are interlinked.

The remaining sections are as follows: section 4.3.2 presents the organisation of data brokers. Section 4.3.3 describes the research approach; Section 4.3.4 explains the findings and discussion. Lastly, Section 4.3.5 concludes the study.

4.3.2 Data Brokers as an Organisation

Data brokers are *intermediaries* in *data management* by connecting data providers and consumers (see Figure 4.7). They work like distributors of manufactured goods (Sebastian-Coleman, 2013). Data brokers *collect* data from providers and *distribute* it to data consumers (see Figure 4.7). They provide confidence regarding the data's use (Janssen & Singh, 2022).

Data brokers can be individuals or units working together as a *data processing ecosystem* (Janssen & Singh, 2022). In this context, a data broker must be a "unit, " not an "individual". It can manifest as both a formal and informal unit. Formal means that top management establishes the unit to address data needs. It occurs when the organisation perceives that the task to address data needs is regular and repetitive - just like a *routine* (Feldman & Pentland, 2003). Informal means that the unit is emergent, assembled by operational employees to support specific data needs. Informal units occur when the organisation perceives the task as unique and temporary– just like a *project* (Schwalbe, 2021).

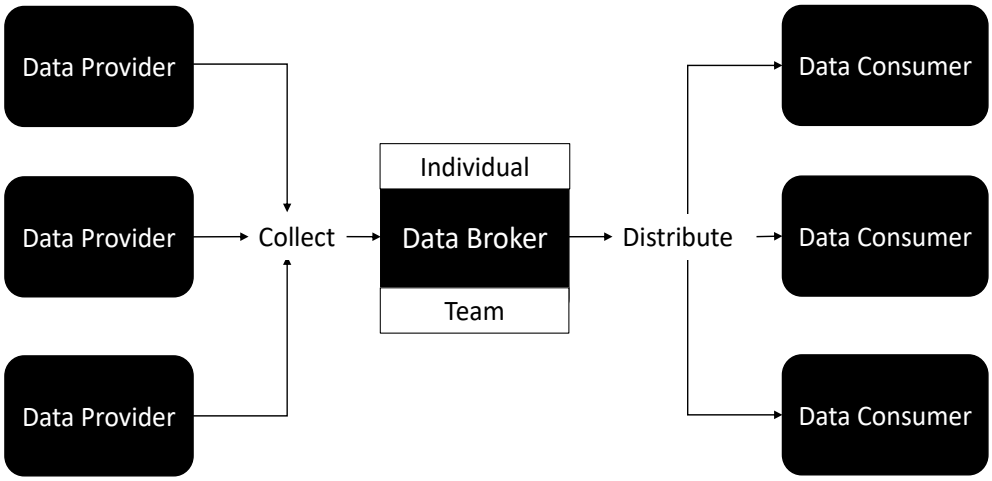

Figure 4.7 A data broker in an organisation

As an emergent unit, the unit is off the organisational structure map. It consists of employees that act as data provocateurs. These employees (data provocateurs) are the primary audience for this study. They are "*individuals who proactively address data (issues), disrupt them by advancing a data quality agenda, and challenge the status quo by questioning how they deal with data"* (Wibisono, Sammon, & Heavin, 2022c). As Redman (2016a, p. 2) said*: "everyone whose job depends on data"* must *"see themselves as a potential provocateur".*

4.3.3 Research Approach: Data Gathering and Analysis

This study conducts field studies in five organisational units that act as data brokers to satisfy different reporting periods (see Table 4.11). They collect data from data providers (e.g., sugar factories, factory operations, pharmacy units, students, and local government agencies). They analyse and report data to data consumers (e.g., internal and external organisational stakeholders).

This research collects data from June 2021 to June 2022 using online semi-structured interviews. Each interview is between 45 and 60 minutes in duration. The recorded interviews are in Javanese and Indonesian and are transcribed into English. The guidelines are as follows: 1) it selects only operational employees that deal with day-to-day processes, 2) it undertakes document analysis when the documents are shared with us, and 3) it does not undertake in-person observations because of COVID-19 restrictions.

Table 4.11 Field Studies

No	Field Study	Number of respondents	Employees % (Data Broker)	Institution	Reporting Period
1	Plantation Company	6 respondents	85%	QA unit (head office)	Daily
2	Furniture Manufacturer	5 respondents	100%	Administrative Office	Monthly
3	Hospital	5 respondents	100%	Pharmacy unit	Three monthly
4	University	3 respondents	75%	Academic office	Six Monthly
5	Government Agency	3 respondents	100%	Government bureau	Annually

Table 4.12 Text Generalisation

No	Excerpt	1st order	2nd order
1	Yes, we immediately (ask) this. To those employees. Why isn't this filled in? How come it's empty?	Data not filled in	Check *data completeness*
2	We are aided by conditional formatting when we cross-check with friends, assistant managers and heads of affairs.	Cross-check with friends	Check *data consistency*
3	So, in the Google Form, there was a print preview, and the print preview was downloaded, so it was printed and then matched (with the student's data in the system)	Matched data (with student data)	Check *data consistency*
4	So, we take the data from the field of each sugar factory. For example, how old is this sugar cane?	Take data from the field	Check *data accuracy*
5	Well, this is not signed by the supervisor. Well, this (letter) is already electronic. (So, we can check)	Check the supervisor's signature	Check *supervisor validation*
6	I took the reports from my friends. That's what I see. I see this; how strange this is. I checked in more detail. It turns out it is not the same (working) template	It's not the same (working) template	Check *data template*
7	For example, the city has an average of 1000 students. If there are 38 districts, the result is 38000 students. Why does the total number of students in the city data differ from the provincial total?	Check why the city number is different from the provincial number.	Check *data consistency*

Interview questions include: 1) How do you work? 2) What data do you need in your work? 3) What tools do you use to handle data in your work (e.g., an IT artefact or paper)? 4) How do you identify data issues? These questions allow us to understand approaches to identifying data issues within the context of each organisational unit.

This study uses open coding (Corbin & Strauss, 1990) for analysis, as this approach breaks down data analytically from interview texts (Böhm et al., 2004). It identifies, labels, and builds concepts from the texts (Wolfswinkel et al., 2011). First, it analyses the interview texts line-by-line (Holton, 2012). Second, it compares incidents with each other from the texts. It reveals five approaches data brokers may use to identify data issues: check *data templates*, *supervisor validation, data accuracy*, *data consistency*, and *data completeness* (see Table 4.12).

4.3.4 Findings and Discussion

This section elaborates on the positives and negatives of each approach. Also, it explains mental models as the engine to operate these approaches. Lastly, it explains how these approaches are interrelated.

4.3.4.1 Check Data Template

Check a *data template* is an artefactual approach. It checks *data collection templates* (Xian et al., 2012, p. 396) submitted by data providers. Typically, these templates can be on physical paper, digital spreadsheets, or word documents. This approach assumes that the artefact that stores the data helps identify data issues.

So, using the template is necessary, such as conditional formatting in a spreadsheet. One employee (the plantation company) said, *"I can make conditional formatting to make it faster. Then we can also make it from the usual graph. Later I can see whether this does not seem right or not. For example, if I'm wrong, I'll make red in the conditional formatting. So (my work is) faster*". Using the data template helps reduce mental overload for data broker

employees in managing large data volumes from multiple providers. Therefore, it has positives and negatives in identifying data issues.

On the one hand, this approach requires a robust data template (as an artefact) for either analysis or communication.

First, it mandates that all data are available in a single artefact (e.g., spreadsheet, word document). This situation can be problematic because it assumes that everyone knows the correct data types and that the template is designed for only those valid data types. The artefact may not support specific data formats for further analysis (e.g., video, audio, spatial, or database-related formats).

Second, some artefacts rely on the algorithmic procedure (e.g., conditional formatting in spreadsheets). If the algorithm logic fails, only a few employees seem capable of identifying this logic failure. So, similar data issues can go unnoticed in the future.

On the other hand, this approach is straightforward.

First, a data broker can return the data if the data provider submits the data in the wrong data template. So, this approach can avoid further data completeness checks in the later stages of identifying data issues.

Second, this approach can facilitate the identification of a wide range of data issues in later stages. For example, the spreadsheet formula (if well-configured) can detect data anomalies without complex human interventions. Hence, data provider employees can identify emerging data issues before sending them to the data broker employees. Therefore, this approach can prevent data issues from propagating to other units and, more importantly, data consumers.

Third, this approach can share domain expertise in evaluating data. For example, word processor software highlight required text. Conversely, spreadsheet software executes algorithmic procedures (e.g., complex and serial calculations). This approach empowers employees to identify data issues independently with more consistent results in a standardised format.

4.3.4.2 Check Supervisor Validation

Check *supervisor validation* is a political approach. It evaluates whether the data provider's supervisor has validated the data. Thus, it is a check towards a *validation mechanism* (Wiggins et al., 2011) completed by a data provider. It assumes that the data requires supervisor validation to be "correct". This approach happens when a data broker collects data from another data broker (a data provider).

One employee (a government agency) said: "*we cross-checked whether the head has (already) checked (submitted documents) or not. The head checks whether these (data) are proper or not. Next, we (could) continue the process.*" This statement indicates that the supervisor (as a senior manager) agrees with the data. Hence, their approval is necessary to ensure data quality. There are advantages and disadvantages to this approach.

On the one hand, this approach introduces a more prolonged process of managing data. *First*, the validation requirement requires employees to *send and wait* for approvals. The supervisor may not be on standby to always approve data. Consequently, the organisation (data provider) can suffer from poor data timeliness, especially when the data are critical and needed immediately while the supervisor is unavailable. *Second*, this approach may bias data quality, assuming data issues are not there. For example, suppose the supervisor receives more data to approve. In that case, the supervisor can *ignore* or *short-cut* the approval mechanism.

On the other hand, this approach designates clear data ownership to the data provider and brings awareness and data responsibility (Vilminko-Heikkinen & Pekkola, 2019). *First*, it informs that specific data should come from a particular provider. So, this approach helps build a data-ownership culture in the organisation. *Second*, it avoids legal problems produced by versioning. For example, a data provider employee can submit multiple data versions, leading to confusion and legal problems. This approach enables organisations to determine which data version has been agreed upon for distribution.

4.3.4.3 Check Data Accuracy

Data accuracy denotes that "the information is correct" (NCES, 1997, p. 45). That is, the data represents the real world accurately. For example, suppose a sugar factory report indicates that the factory produces 10 tonnes of sugar per quarter. In that case, the reality should indicate the same production amount. Earlier research confirms that data accuracy is an essential attribute of data quality (Nagle et al., 2020; Strong et al., 1997; Wang et al., 1995).

Check *data accuracy* requires access to original data sources. It assumes that these original data sources operate within the organisation. They are the product of an internal process owned by the organisation (not by other parties). For example, when the data capture a machine's attributes, the machine is available in the factory. When the stock is in a warehouse, then the warehouse is accessible. So, data brokers and data provider employees can visit the factory site to compare the reality and the reported data. Thus, they can directly access original data sources for further inquiry.

Without these this assumption, on-site visitation is challenging. For example, one employee (plantation company) said: "*Are the farmers still (planting) sugarcane in the field? If it's not sugar cane (planted in the field) (please do something), (However if) the farmers say they still want to partner with us, we must know in which location. (We must) Check! Where?*".

This approach has positives and negatives.

On the one hand, it demands extra costs for checking multiple data sources or technology investments. If employees must check multiple data sources, which are geographically dispersed, then travel costs occur. Otherwise, the required technology investment increases if the organisation utilises non-human technologies (e.g., drone or remote sensing) to capture the phenomenon (e.g., checking sugarcane fields).

On the other hand, this approach is factual. It establishes a trusted correction of data. Also, it can capture something not reported before. Therefore, the data can better reflect the phenomenon.

4.3.4.4 Check Data Consistency

Data consistency means that "all clients see the same data" (Rodger, 2011, p. 180), regardless of where and how these clients access the data. So, this approach evaluates whether the data are consistent across various accessible data sources (e.g., spreadsheets and documents). Ensuring data consistency across organisations corroborates previous studies that emphasise the importance of data consistency as an attribute (Wang & Strong, 1996).

Check *data consistency* assumes that these multiple data sources are reliable and accessible for comparison. For example, one employee (university) said: "*We contact (students) concerned. We let (them) know. So, there is a difference between the ID card and the last diploma (the student). So, we suggest the student look at the history. (We asked the student to check) starting from (their) elementary school diploma to the last one? Well, where are the mistakes*?" This study finds there are two methods of checking inconsistencies. First, an employee compares the data with non-aggregated data from other sources. Second, the employee compares data with aggregate data from other data sources. The employee can use the data if the data proves consistent across data sources.

There are positives and negatives associated with this approach. On the one hand, it is prone to cognitive overload for employees. First, data can be stored in different formats across various artefacts, leaving employees with the daunting task of transforming the data for comparison. Second, locating reliable benchmark artefacts can be time-consuming, and there is no guarantee that they are up-to-date or trustworthy. As a result, employees may spend hours scouring for the right artefacts. These hurdles can make data comparison a complex and frustrating task, highlighting the importance of having efficient systems in place. *Third*, the intended data can be available as a fraction of "larger" data.

The employee must first find and isolate the intended data. Hence, it is time-consuming and inefficient.

On the other hand, this approach allows employees to find the "best" data. *First*, it allows the organisation to reflect across various data sources. For example, data can have multiple versions across data sources. Consequently, data broker employees can synthesise these versions or filter unrelated versions. *Second*, sometimes two artefacts introduce two different versions of the same data. This approach can help organisations weigh the relative importance of the data based on 1) the produced data and 2) the priority of the artefacts that store data.

4.3.4.5 Check Data Completeness

Data completeness refers to the extent to which "*the stable data preserves the information we need*" (Johnston, 2014, p. 278). It shows that the fulfilment of each data attribute is complete (not partial) to capture realities. The fact that organisations use data completeness confirms that previous research suggested that data completeness is a crucial attribute (Nagle et al., 2020; Redman, 1998). This approach assumes that *blank data are* unacceptable. One employee (plantation company) says: "*I'll return the spreadsheet if it's empty*." It has several positives and negatives due to its simplicity.

On the one hand, check *data completeness* does not explain why the required data are missing. So, the data broker employees can only suggest fulfilling the missing data. However, when a thorough explanation is needed, the organisation must organise a forum that gathers all data participants. When the blank data are submitted with specific values, they (still) do not guarantee an accurate account – because the reality may change or become inaccessible.

On the other hand, check *data completeness* does not need to examine other data sources. So, it does not require complex interpretations to determine whether the organisation has data issues. Further, it reduces knowledge requirements (e.g., statistics ability) in detecting data issues. This approach works well in a large volume of data to check.

4.3.4.6 Mental Models to Operate the Process

Mental models are *judgment* or *subjectivity in the production of data* (Strong et al., 1997, p. 105). They are frameworks established in the minds of humans that guide the completion of data tasks. For example, employees compare the data with the "*best data version"* in their mental models. One employee (plantation company) said: "*If you don't understand (what is going on). You don't know which numbers wrong or which numbers are is too high. That is (absolutely) problematic*." Despite their importance, mental models can be imperfect as they only capture partial data attributes, which can overlap, complement, or contradict each other.

On the one hand, mental models require a mature understanding of *data* and the *process* that produces the data. These understandings develop during employees' work, training, and life experiences (Weick et al., 2005). For example, one employee (furniture manufacturer) said: "*So I must (repeatedly) look (at the data) again and again. I always (do it). So, (I) understand. Finally, I can memorise it, (because) it is my everyday work. I must see (the data) one by one*." Therefore, an organisation must train new employees to oversee and work with various data types. This mental model building requires a prolonged time to perfect. Novices can mistakenly identify non-data issues as data issues and vice versa. Therefore, other employees must always double-check the interpretation. So, novices can develop the "right" mental models. One employee (hospital) says: "*Yes, (we) must (continue to) train employees, and it must be unified with the service. (After some time), (this mental model) becomes a reflex*".

On the other hand, mental models facilitate an "on-the-fly" assessment of data issues. It quickly identifies data issues and proposes potential solutions. Therefore, resourceful mental models can efficiently solve data issues independent of certain artefacts. Hence, they promote better artefactual flexibilities.

4.3.4.7 A Flow Diagram to Identify Data Issues

This study reveals a flow diagram that articulates all approaches to materialize. The flow applies several assumptions. First, this study assumes the data remains stable throughout the examination process. Second, this study places humans at the forefront of identifying data issues instead of relying solely on machines. Lastly, this study acknowledges that human subjectivity plays a crucial role in examining data, as pointed out by (Kooper et al., 2011). By understanding these assumptions, a researcher can better appreciate the complexities of ensuring data quality.

Furthermore, this study posits that the flow must start with a check data template (see Figure 4.8). This approach sets up the context for other approaches to manifest. One employee (plantation company) says: "*First, I took the report from my friends on the package. I see this. I checked (the data) in more detail. It turns out (that it comes from a document that) doesn't match the template*".

Check *data template* triggers all approaches: check *supervisor validation, data accuracy, consistency, and completeness* (see Figure 4.8). Regardless of what approach is executed, *mental models* pre-exist in all approaches. They guide employees in identifying data issues retrospectively (see Figure 4.8). They facilitate a continuum in checking data. As data broker employees typically do not produce the data, this continuum is essential to identify the locus of data issues. So, it is crucial as a *curative* practice.

Furthermore, data can be part of several approaches for identifying data issues (see Figure 4.8). One employee (plantation company) says, "*For example, the loss of factory A is not reasonable (from the mental model). It is too high compared to other factories. We go down for supervision (to the field). We check the problem: wrong data entry, analysis, or something else*."

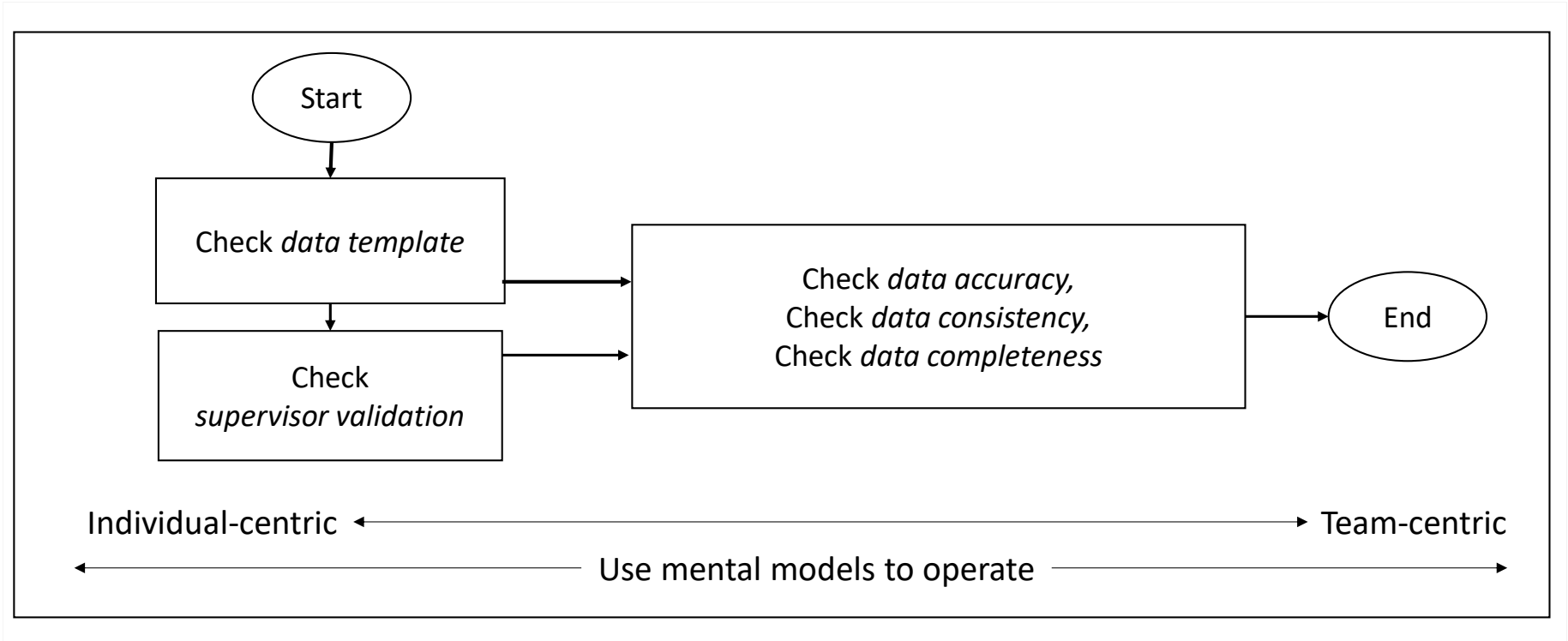

Figure 4.8 The data issues identification flow

Check data *accuracy*, *consistency*, and *completeness* manifest as individual- and team-centric activities. So, they produce personal and joint interpretations of data issues. They are negotiable, contestable, and mutually co-constructed. Some employees are more experts than others, and data issues can be sophisticated. So, organisations establish "extra checking layers".

One employee (plantation company) indicates: "*Data from Sugar Factory 1 to Sugar Factory 9 is taken. The next step can be filtering (by me). Then I give it to the level above me. In this case, the one who did was XX. Afterwards, the data can be sent to YY for further evaluation (as a report) for top management*." As multiple employees set up these layers, the flow becomes more resource-intensive.

Identifying data issues stops if employees feel they have achieved order, clarity, and rationality against the data. Therefore, employees can demand *more* or *different information* from other sources to achieve this feeling. It resolves any ambiguity and equivocality experienced by earlier identification flow. Identifying data issues can take time; however, it does not guarantee that an organisation can have quality data for two reasons. First, the phenomenon and sources may become inaccessible over time. Thus, it makes the data comparison with reality challenging. Second, the flow alone cannot address issues in the original data sources, potentially leading to the recurrence of similar data issues in the future.

4.3.5 Conclusion

This research examines how data broker employees identify data issues in organisations. This study finds that employees use five approaches to identify these issues. The approaches are check *data templates, supervisor validation, data accuracy, data consistency,* and *data completeness.* It explains the advantages and disadvantages of each approach. Next, it introduces a flow diagram explaining the associated approaches.

4.3.5.1 Theoretical Contributions

This research provides several contributions to data quality research. First, it challenges the mainstream assumption in data quality research that addressing data issues must be *preventive*. It demonstrates that this process can also be *curative*. As to theoretical implications, the idea of *a curative* process facilitates the emergence of *curative-driven* data governance structures, policies, and rules. Their operations were missing from current data governance or data quality literature.

Second, this study illustrates five approaches to identifying data issues. It describes each approach and shows how they are mutually exclusive and exhaustive in identifying data issues. Therefore, each approach is a theory for analysing – Theory Type 1 (Gregor, 2006, p. 622). These approaches facilitate further theorising how organisations solve data issues after identifying them—for example, data completeness, accuracy, consistency, and availability.

Third, it conceptualises how these approaches are connected as a single flow. In doing so, it opens the black box of "evaluate data" as one type of workaround-centric data activities (WCDA) (Wibisono et al., 2020, 2022b, 2022c). Other data activities include *compile*, *transfer*, *retrieve*, and *store* data (Wibisono et al., 2022a). These data activities connect and assemble patterns of action to solve data issues. Further, it argues that identifying data issues is one element of "evaluate data." A subsequent process called "*formulating data solution*" can follow as it is complete.

Therefore, identifying data issues can evolve into a complex web of actions. It explains conditions that facilitate the occurrence of each approach. So, this flow diagram is a theory for explaining – Theory Type 2 (Gregor, 2006, p. 624). This flow diagram facilitates further theorising on data consequences, such as data issues and their economic effects. For example, what costs emerge from these data issues? How do organisations identify these costs? How do they categorise them?

4.3.5.2 Managerial Implications

The research shows that identifying data issues is a mindful process. Data provocateurs may execute two or more approaches to identify data issues (not to mention the process of fixing them). So, the entire process of identifying and solving data issues can be time-consuming and resource-intensive. Therefore, this study suggests two key recommendations.

First, an organisation must automate its business processes (from data capture to reporting). For example, the organisation can use IoT and Artificial Intelligence to capture real-time data. These data can be in a reliable information system (e.g., ERP) for further processing and reporting. Thus, the organisation can avoid data timelines and wrong data entry by employees. Research suggests that poor data practice can continue even after introducing an ERP (Drum et al., 2017).

Second, data provocateurs can combine approaches to examine the data thoroughly. This skill can also elevate their capabilities in analysing data. Over time, mastering multiple approaches can help the organisation tackle data issues before they manifest.

4.3.5.3 Limitation and Further Research

This research has limitations. *First*, this research only collects data from data broker employees (not data providers). It may overlook some approaches for identifying data issues. However, data brokers usually identify errors in the data. The flow diagram presented in Figure 4.8 includes the fundamental approaches for identifying data issues. *Second*, this study does not consider *emotions and power* (Maitlis & Christianson, 2014) in developing the flow diagram. Employees may be preoccupied with their emotions or power during data examination, and these factors may alter the flow. These factors can also introduce an innovative approach to identifying data issues.

Also, this research highlights future research opportunities. *First*, researchers can examine the impact of emotions and power in identifying data issues. Hence, data provocateurs can devise new policies to deal with data

issues. *Second*, some data issues require a more elaborate approach as a chain of actions. Thus, researchers can examine data issues and their chain of action. Researchers can develop a taxonomy of data issues by answering additional questions such as what are the differences? What are the similarities? What are the approaches frequently observed in these data issues? This taxonomy can be helpful to prioritise data issues. *Third*, approaches can introduce actions to fix data. What are the actions to fix data? How are these actions related to data issues? How are these actions connected? Thus, researchers can develop a taxonomy of data issue solutions.

In the end, identifying data issues is essential for data governance success, such as improving *data quality* (Benfeldt et al., 2019; Janssen et al., 2020; Merkus et al., 2019) and meeting *compliance* requirements (Fisher, 2009; Janssen et al., 2020). However, identifying data issues is naturally *curative*. It does not solve problems at the data source. So, future data issues may occur. Requiring additional resources to re-identify and resolve them. Therefore, the optimum approach is to prevent these data issues from materialising. One strategy is to automate data capture and related business processes. By doing so, the organisation can allocate employees for other, more value-added tasks.

4.4 Conclusion

This chapter examines the empirical investigation of five field studies. The first two sections focus on two data issues: data availability and data accuracy and the use of workarounds as the unit of analysis (see Table 4.13). Section 4.1 reveals that data availability issues introduce three patterns of action: dual inspection, prudent control, and mindful handling. Similarly, Section 4.3 reveals that data accuracy issues introduce three patterns of action: field inspection, fast authorisation, and gold standard making (see Table 4.13).

The first two sections reveal that "evaluate data" is the common denominator of all identified patterns of action. This data activity manifests consistently across these patterns. Consequently, this study looks at how data

evaluation processes work. Notably, it tries to hypothesise how employees identify data issues.

Finally, Section 4.3 examines how employees identify data issues. It uses data from five organisations and employs WCDA *"evaluate data"* as the unit of analysis (see Table 4.13). Organisations may use five "checking" approaches: *check* data template, *check* supervisor validation, *check* data accuracy, *check* data consistency, and *check* data completeness. This study discusses each approach, theorises how they relate to one another and considers the contributions to data quality theory and practice.

Table 4.13 Empirical investigation summary

No	Section	RQ	Research Question	Unit of Analysis	Output
1	4.1	RQ4.	What are *the WCDA patterns* of action triggered by data availability issues?	Workarounds	1. Dual inspection 2. Prudent control 3. Mindful handling
2	4.2	RQ5.	What are *the WCDA patterns* of action triggered by data accuracy issues?	Workarounds	1. Field inspection, 2. Fast authorisation, 3. Gold standard making
3	4.4	RQ6.	How do employees *identify data issues* in WCDA?	WCDA (Evaluate Data)	*Checking:* 1. Data template 2. Supervisor validation 3. Data accuracy 4. Data consistency 5. Data completeness

The next chapter summarises the theoretical insights arising from this work. The chapter revisits each research question and describes theoretical contributions and managerial implications. Eventually, it presents the limitations of the research and highlights potential future research.

Chapter 5
Conclusion

5.0 Introduction

This chapter aims to conclude the results and findings of this study. It summarises how the study answered each research question. Then, theoretical contributions and managerial implications are outlined. Limitations of the study and recommendations for future research are also discussed.

This research highlights the importance of understanding an organisation's approach to handling data issues. However, this study notes that practices that address data issues after they occur (*curative* practices) are not as well researched. These *curative* practices are similar to the idea of *hidden data factories* (Redman, 2016b). Studying *curative* practices can increase our knowledge about dealing with data issues in everyday events, such as poor IT infrastructure (Born & Krönung, 2016; Stevenson et al., 2018), poor software usability (Baysari et al., 2018; van den Hooff & Hafkamp, 2017), poor software functionalities (Ibrahim et al., 2019; Van de Weerd et al., 2019), and employee coordination problems (Niazkhani et al., 2011; Walterbusch et al., 2017). (Redman, 2016b). Therefore, this research turns to the workaround literature because it contains several examples of creative practices for addressing data issues. However, regarding data governance, these creative practices are not the primary topic of conversation.

This study tries to understand these creative practices to close this research gap. It describes these behaviours as workaround-centric data activities (WCDA). Furthermore, it derives WCDA a priori constructs from workaround literature (see Chapter 2, Section 2.1).

Furthermore, this research sees data governance as a “process”, not an “authority”. This notion contrasts with the traditional view of data governance. As a result, this study black boxes many elements widely discussed in traditional data governance literature. For example, data strategy, roles, rules, and organisational structures are some elements (Abraham et al., 2019; Al-

Ruithe et al., 2018; Koltay, 2016; Romero et al., 2019). This study only focuses on how managing data manifests in practice.

In capturing how organisations manage data, this study develops a notation and its modelling rules (see Chapter 3, Section 3.10). These notation and modelling rules shape the empirical works to theorise the WCDA *patterns of action* (see Chapter 2, Section 2.1). The following section revisits each research question and highlights the findings, theoretical contributions, and managerial implications.

5.1 Revisiting the Research Objective and Questions

This section revisits the previously mentioned research objective and questions in Chapter 1 and discusses the findings. In Chapter 1, the research objective was stated as follows:

Research Objective:
To explore WCDA *patterns of action* as *curative practices* to address *data issues*

The empirical investigations (see Chapter 4) address this research objective. However, they focus on the two most prominent data issue types: *availability* (see Chapter 4, Section 4.1) *and data accuracy* (see Chapter 4, Section 4.2). From the produced patterns of action, one data activity (*evaluate data*) is selected to understand how data broker employees identify data issues (see Chapter 4, Section 4.3).

5.1.1 Workaround-Centric Data Issues (RQ1)

In answering this research question, 62 empirical articles from the IS domain were analysed (see Chapter 2, Section 2.1. Based on this analysis, a taxonomy of WCDI is proposed (see Table 5.1).

RQ1. What are Workaround-Centric Data Issues (WCDI) in organisations?

Table 5.1 Taxonomy of Workaround-Centric Data Issues (WCDI)

No.	Workaround-Centric Data Issues	RQ 1	RQ 2	*Total*
		Cause	Create	
1	Data availability	11	15	26
2	Data accuracy	5	19	24
3	Data security	1	16	17
4	Data consistency	2	13	15
5	Data access	9	6	15
6	Data presentation	13	2	15
7	Data completeness	3	10	13
8	Data duplication		11	11
9	Data meaning	2	7	9
10	Data privacy		9	9
11	Data leak		8	8
	Total	46	116	162

This taxonomy contains eight data issues that workarounds cause and eleven data issues that workarounds create. As presented in Table 5.1, there are two primary data issues: *data availability* and *data accuracy*. As these issues come from empirical publications, one can assume they are the most prevalent data issues in practice.

5.1.1.1 Theoretical Contributions

This research is the first study to examine WCDI in the context of information systems. By highlighting these multiplicative effects retrieved from the literature, this study questions the waterfall-style logic of the Theory of Workarounds (Alter, 2014).

As a widely-cited theory, it discusses the origins of a workaround in a historical sequence. It recognises that a workaround might have "local and broader consequences" (Alter, 2014, p. 1055). However, it fails to recognise that some consequences (e.g., data issues) might lead to another workaround.

These consequences may lead to additional data issues. As a result, a vicious cycle is created.

So, this study revises the Theory of Workarounds (Alter, 2014). It shows that data issues can cause workarounds, and workarounds can create data issues. Understanding these vicious cycles is necessary for theorising how a workaround evolves, develops, spreads, and diminishes across units. Also, the Workaround-Centric Data Issues (WCDI) taxonomy summarises the current theoretical insights regarding WCDI from IS literature. This taxonomy aids researchers and managers in identifying WCDI within an organisation.

5.1.1.2 Managerial Implications

This study discovers that many data issues may be resolved by concentrating on user elements (such as work ethics, habits, knowledge, and competence). Therefore, to handle WCDI, an organisation must nurture an understanding of the deliverable data value from its formal IS at all levels. By taking this measure, workarounds that compromise organisational data can be avoided.

5.1.2 Workaround-Centric Data Activities (RQ2)

In answering this research question, 62 empirical articles from the IS domain were analysed RQ2 (see Chapter 2, Section 2.2). Based on this analysis, this study produces a Taxonomy of WCDA.

RQ2. What are Workaround-Centric Data Activities (WCDA) in organisations?

This taxonomy presents nine data activities across three types of workarounds. One of the activities (*enter data*) is broken into six constituent parts. Furthermore, six data activities are the most frequently occurring. They are *transferring, storing, retrieving, entering data (late), entering data (inaccurate),* and *analysing data*. The taxonomy also reveals that *'informal system use'* is the most frequently occurring workaround.

Table 5.2 Taxonomy of Workaround-Centric Data Activities (WCDA)

			Workaround-Centric Data Activities														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	
			Enter data														
			Late	Inaccurate	No Enter	Incorrect (location)	Incomplete	Delegated	Transfer data	Store data	Retrieve data	Analyse data	Compare data	Manipulate data	Consolidate data	Transform data	*Total*
Types of Workarounds	1	Informal system use							70	62	44	16	12	7	5	5	221
	2	Formal system use	36	22	13	11	7										159
	3	Human proxy use						7			7	3					17
Total			96						70	62	51	19	13	7	5	5	

5.1.2.1 Theoretical Contributions

This research represents one of the first studies examining WCDA in the context of Information Systems (IS). The Workaround-Centric Data Activities (WCDA) taxonomy summarises the current theoretical insights regarding WCDA from IS literature. The taxonomy defines a set of constructs representing the data activities connected to workarounds (in an organisational environment) where the nature of WCDA is currently poorly understood. This taxonomy aids researchers and managers in identifying the nature of WCDA within an organisational context. Given these facts, this taxonomy functions as Theory Type I – Analysis (cf. Gregor, 2006). Hence, this research contributes to the workaround literature.

5.1.2.2 Managerial Implications

There are numerous approaches to dealing with problems introduced by data activities. First, employees must know the value chain (Porter, 1985). Employees not well-versed in the value chain may engage in meaningless WCDA. Therefore, the organisation must organise frequent training to educate employees on how data moves between departments and divisions.

Second, an employee's data discipline makes it easier to enter high-quality data into the formal system(s) "on time". If not, data timeliness becomes problematic for an organisation because the data are unavailable when needed (Jagannath et al., 2018). As such, one's self-discipline and other employees' data discipline are strongly connected. As a result, an organisation must establish specific goals for task completion, and personnel must prioritise the data entry task as one that always needs to be completed.

Third, employees require working knowledge and skills (Azad & King, 2012). They need to comprehend how the organisational artefact may help the business process and how it should manifest. For instance, an employee must thoroughly comprehend how the data should reflect actual transactions while

inputting data. Additionally, the individual must understand where to enter data on the official system.

5.1.3 Modelling WCDA (RQ3)

In answering this research question, the narrative network (NN) is extended to model WCDA (see Chapter 3). This study proposes five WCDA modelling rules and a step-by-step NN construction guide (see Table 5.3).

RQ3. How are modelling rules used to model WCDA?

Table 5.3 Rules to model WCDA.

No.	Statement
Rule #1	A narrative fragment must come from a process actor.
Rule #2	A narrative fragment has three attributes: actor, action & resource.
Rule #3	All attributes in a narrative fragment establish the action type.
Rule #4	A narrative fragment must contain a data activity.
Rule #5	A narrative fragment data activity must follow a standard naming convention.

Table 5.4 Step-by-step to construct a narrative network.

No	Step	Note
1	Choose a process and define its boundary	Focus on the "purpose."
2	Adopt a point of view	*Rule 1*
3	Collect the narratives and code the fragment	*Rule 2, Rule 3, Rule 4, Rule 5*
4	Relate code with sequences	Visualise the NN

These rules and step-by-step guides enable data provocateurs to represent, observe, and analyse workarounds and their associated data activities (see Table 5.4). They provide plausible pictures for data governance by

visualising the organisational reality and highlighting WCDA patterns of action.

5.1.3.1 Theoretical Contributions

This research leads to new insights relevant to workaround literature, particularly WCDA as an organisational phenomenon. This study provides notation and guidelines for modelling and visualising WCDA. Because the research is the first to do so for workaround contexts, these guidelines serve as the originality of the work. So, these guidelines serve theory for design and action - Theory Type 5 (Gregor, 2006, p. 628). These rules supplement the generic principles for using the narrative network offered by Hayes et al. (2011), Yeow and Faraj (2011), and Feldman and Almquist (2012).

Furthermore, this modelling tool provides *a standard vocabulary* widely understood by multi-level organisational stakeholders (Pentland et al., 2017). In this scenario, the narrative network is represented as sequential relations between activities in chronological order (Pentland et al., 2017). Because it is chronological, the sequential relationships are easy to follow for each stakeholder in a team.

5.1.3.2 Managerial Implications

Modelling WCDA can help an organisation build a plausible picture of data governance. For example, it has a better conversation about managing data and by whom. Why do specific data issues materialise while some others do not? What are the causes? This understanding can improve data-related process transparency, directly impacting data quality. Subsequently, these insights can inform managers in improving data governance initiatives. Hence, they can increase data values and minimise data-related costs and risks as time passes.

5.1.4 Patterns for 'Data Availability' Issues (RQ4)

A review in Section 2.1 suggests that *data availability* is the most occurring data issue in workaround literature. So, this insight facilitates RQ4.

RQ4. What are the WCDA patterns of action triggered by data availability issues?

In answering this research question, the WCDA patterns of action, triggered to solve data availability issues, are presented (see Chapter 4, Section 4.1). These patterns of action are observed in a field study of a Quality Assurance (QA) unit of an Indonesian sugar plantation company. This unit serves as a data broker, which manages various data from data providers (e.g., sugar factories).

First, a data broker is viewed as an intermediary in data management. It connects the data provider and data receiver. They function similarly to manufacturers' distributors (Sebastian-Coleman, 2013). It oversees the data quality before the data are used for subsequent users. As a result, it assures how the data may be utilised (Janssen & Singh, 2022).

Second, a data provider is viewed as the originator of the data. It supplies data that a data broker can check. In this study, all patterns come from data brokers.

.

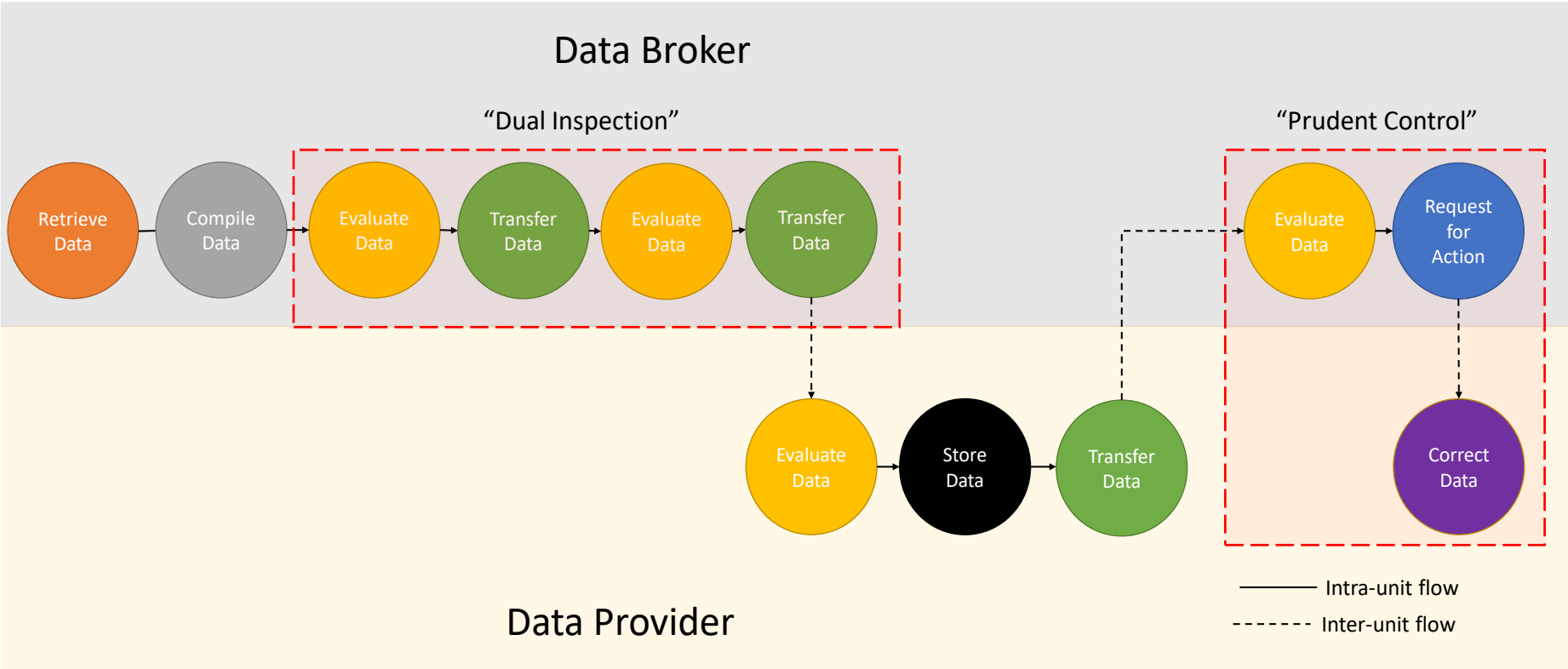

Figure 5.1 Dual Inspection and Prudent Control Patterns

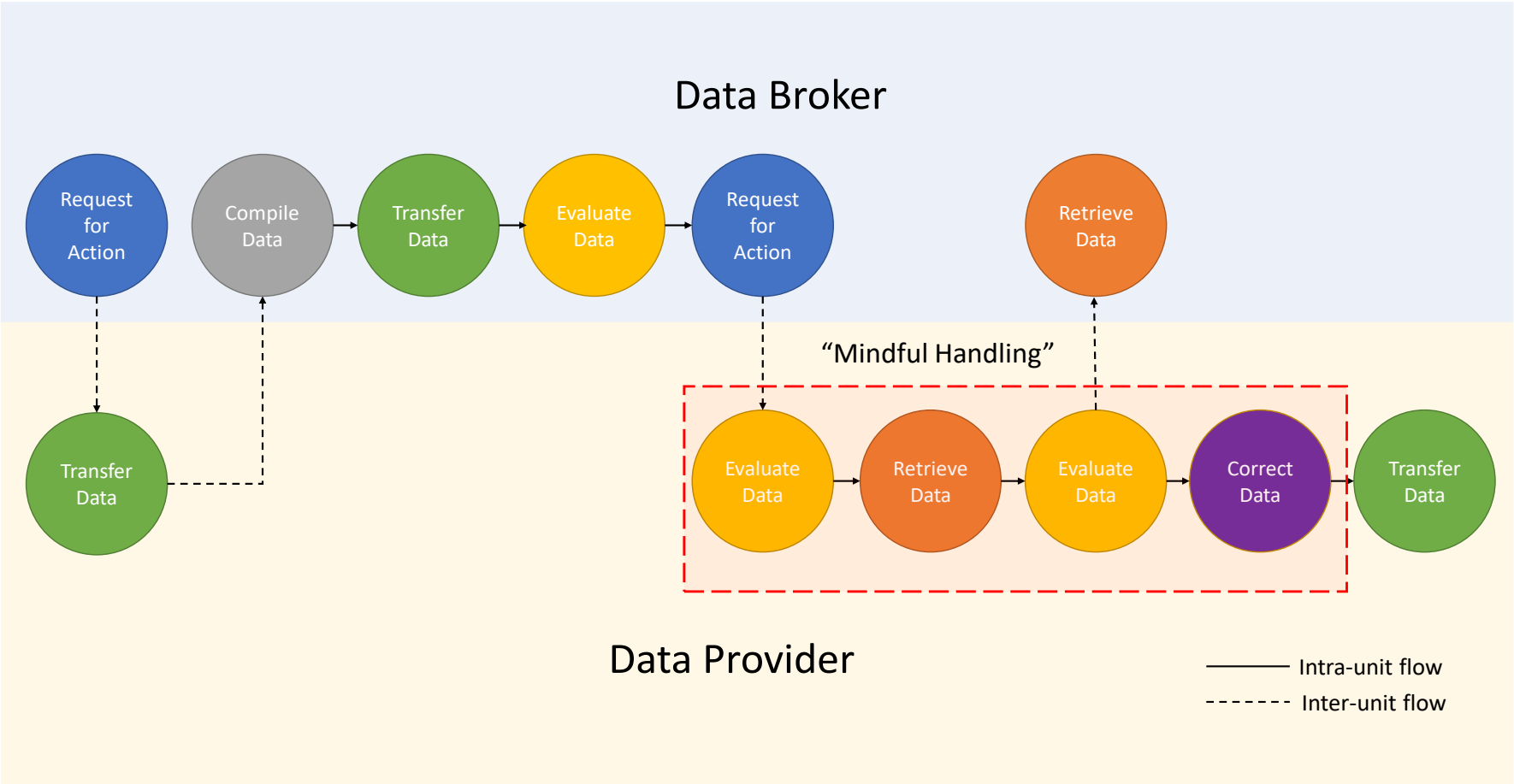

Figure 5.2 Mindful Handling Pattern

Mindful Handling is a pattern in which an employee acts and reflects on what is happening (see Figure 5.2). WCDA's first "evaluate data" allowed one to understand the problem. Then, "retrieve data" enables access to the primary data source. Finally, "correct data" enforces deliberate data alterations.

5.1.4.1 Theoretical Contributions

This study offers fresh perspectives on the workaround literature concerning WCDA as an organisational phenomenon. It illustrates how the NN technique may be used to visualise action patterns. It specifies seven WCDA and three patterns of action (e.g., *dual inspection*, *prudent control*, *mindful handling*) to address *data availability* issues. Therefore, it improves knowledge of WCDA and their connections.

Hence, these three patterns serve as an explanation theory - Theory Type 2. (Gregor, 2006, p. 624). These patterns highlight the importance of WCDA, which earlier workaround research had undervalued. As a result, the theoretical contribution is significant and unambiguous for workarounds and data governance research.

Within this field study, the WCDA modelling rules and step-by-step guide are used to uncover the patterns of action. Three WCDA patterns emerge related to data availability issues: *dual inspection*, *prudent control*, and *mindful handling* (see Figure 5.1 and Figure 5.2).

Dual inspection (see Figure 5.1) may help identify problems with massive data silos because several employees look at the same data. This approach enables the organisation to assign the most qualified employee(s) to manage the data.

Prudent control is a trilateral arrangement placing "assess data" before "request for action" and "correct data" (see Figure 5.1). Since it includes the broker and its data provider, it lessens and controls friction between these units brought by the data issue.

5.1.4.2 Managerial Implications

The managerial implications are most relevant for aspiring data-driven organisations that run multiple centralised and decentralised systems to support their operations. Furthermore, the transformation to a data-driven organisation has become more prevalent. Consequently, multiple system landscapes propagating data availability issues can force employees to execute WCDA to meet their "good quality" data needs. In this regard, this study raises awareness of data availability issues in aspiring data-driven organisations.

As for recommendations, it suggests that every organisation automates (real-time data entry) repetitive and predictable processes by using IoT and sensors. However, if human action for data entry is required, it suggests the organisation enhances employee data discipline. One strategy is to incentivise employees to enter data on time. By doing so, data availability issues can be avoided.

5.1.5 Patterns for 'Data Accuracy' Issues (RQ5)

According to a review in Section 2.1, data accuracy is the second most common data issue in the workaround literature. As a result, these insights aid the emergence of RQ5.

RQ5. What are the WCDA patterns of action triggered by data accuracy issues?

The WCDA patterns of action triggered to overcome data accuracy issues are described (see Chapter 4, Section 4.2). These patterns of action are observed in three field studies in Indonesian settings, including a university, a government agency, and a plantation company.

Three WCDA patterns address data accuracy issues: *field inspection, fast authorisation,* and *gold standard making*.

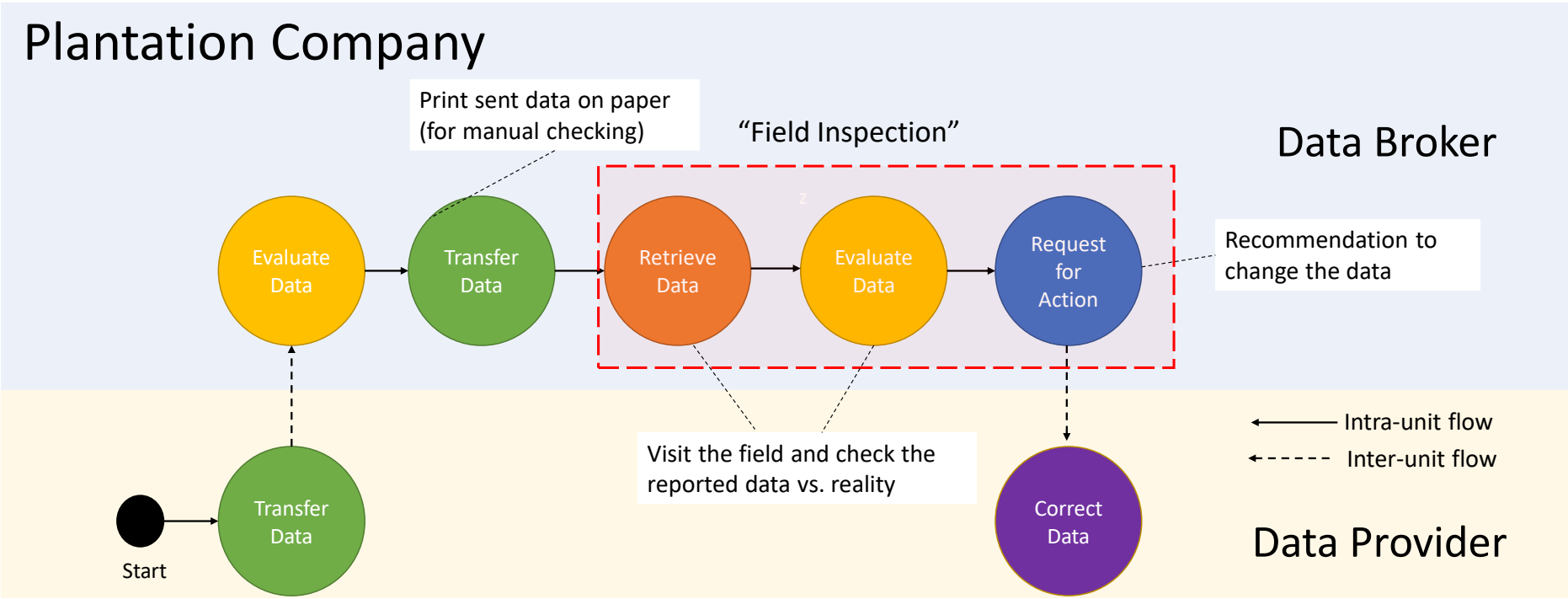

Figure 5.3 Field Inspection Pattern

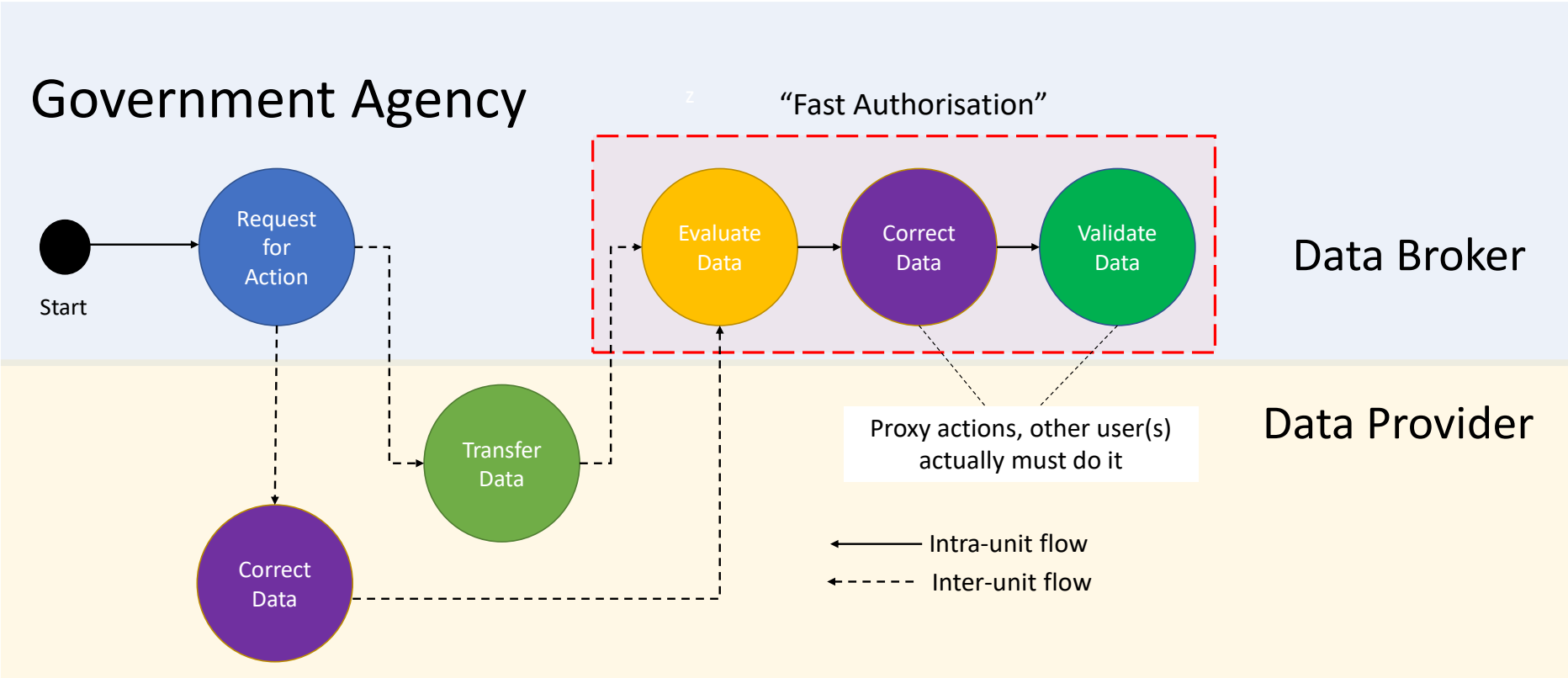

Figure 5.4 Fast Authorisation Pattern

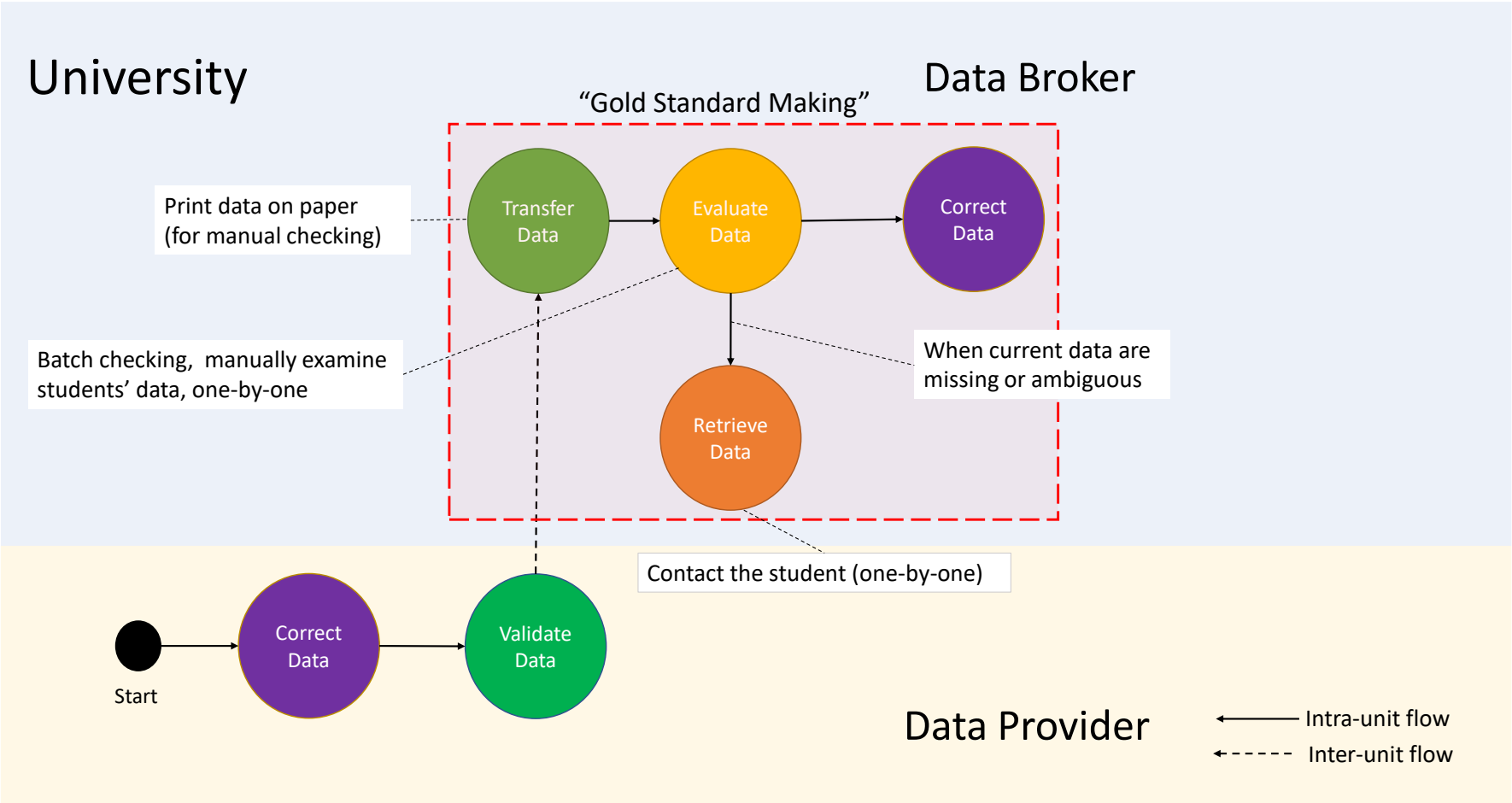

Figure 5.5 Gold Standard Making Pattern

In the plantation company, *Field inspection* is observable (see Figure 5.3). It illustrates how employees tackle the data accuracy issue. This pattern minimises the bias brought forth by inexperienced data providers or producers. The pattern's call for action also allows data provider employee members to evaluate the data.

In the government agency, the *Fast Authorisation* pattern is observable (see Figure 5.4). This pattern offers both advantages and disadvantages. This pattern allows the organisation to respond rapidly to data accuracy issues. As a result, it is suitable for discerning data users who do not require additional technical training.

In the university, *Gold Standard Making* is observable (see Figure 5.5). This pattern is fast as it eliminates contact with data providers (e.g., students) and makes the process more efficient.

5.1.5.1 Theoretical Contributions

This research advances the understanding of WCDA and their relationships (as patterns of action) to address data accuracy issues. It finds six WCDA used to overcome data accuracy issues: *correct* data, *evaluate* data, *transfer* data, *retrieve* data, *request for action*, and *validate* data. These six activities are linked to each other and establish three patterns of action: *Field Inspection*, *Fast Authorisation*, and *Gold Standard Making*.

By observing these three patterns, this research increases understanding of the WCDA and their linkages. These three patterns serve as an explanation theory - Theory Type 2 (Gregor, 2006, p. 624). This finding emphasises the significance of WCDA, which has previously been neglected in workaround research. As a result, the theoretical contribution to research on workarounds and data governance is considerable and unequivocal.

5.1.5.2 Managerial Implications

Theoretical insights show that data accuracy is difficult for managers and system designers to grasp. As a result, enhancing data accuracy necessitates deliberate measures. It demands a comprehensive elaboration of the data. It also requires extensive system design knowledge and continual oversight (for all data aspects). Furthermore, problems that create or propagate data accuracy issues must be addressed constantly.

An organisation must automate ordinary, repetitive day-to-day procedures to solve data issues. The organisation can automate the process using industrial-driven technology such as Robotic Process Automation (RPA) or Business Process Management Systems (BPMS). As a result, an organisation may increase productivity, save expenses, eliminate data inaccuracies, and save personnel time.

5.1.6 Patterns for Identifying Data Issues (RQ6)

Previous sections show that the most prevalent WCDA is "*evaluate data*" (see Chapter 4, Section 4.3). In this context, *evaluate data* is a composite WCDA and comprises *identifying data* and *formulating data issue solutions*). So, the following RQ is posed:

RQ6. How do employees identify data issues in WCDA?

The patterns of action come from five Indonesian field studies (a plantation company, a government agency, a university, a hospital, and a furniture manufacturer). They are analysed to establish how data broker employees identify data issues. The WCDA *evaluate data* is an example of a commonly used *curative practice* for data governance.

This research reveals that data broker employees can execute five approaches to *evaluate data*: check *data template*, *supervisor validation*, *data accuracy, data consistency,* and *data completeness* (see Figure 5.6).

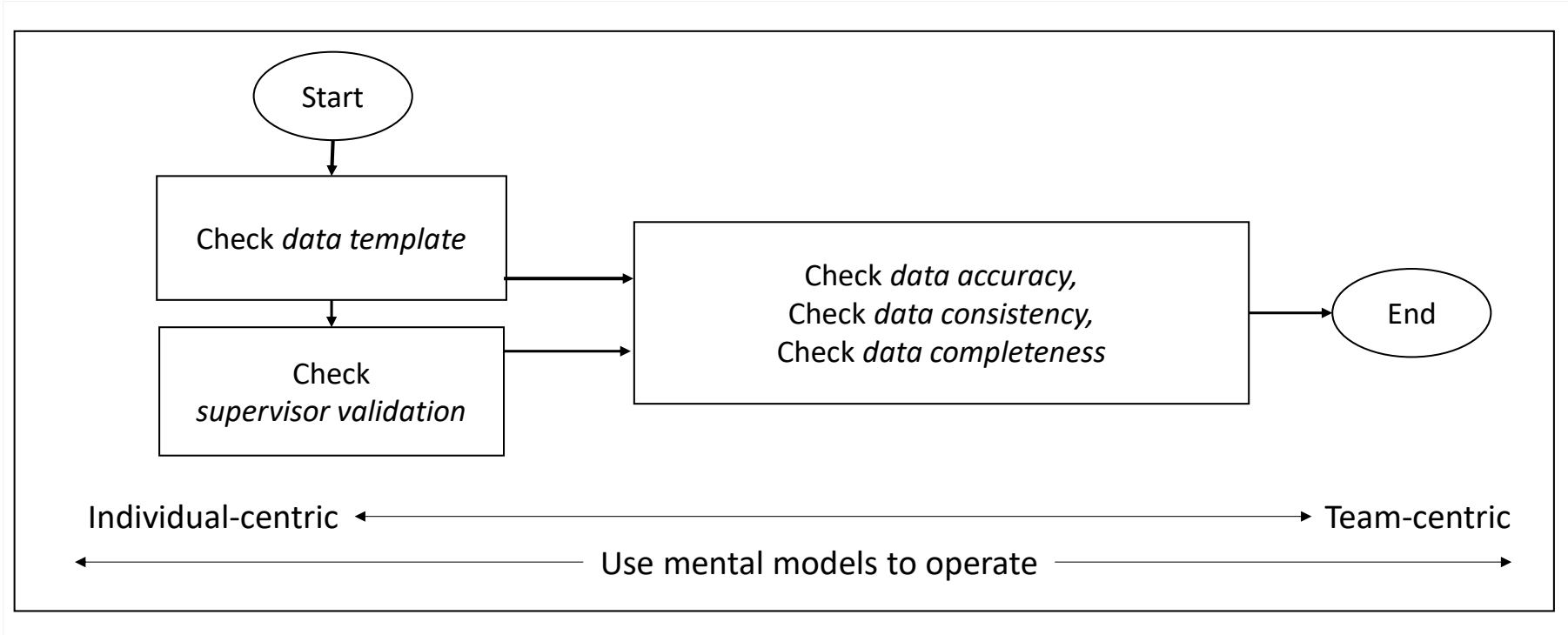

Figure 5.6 Flow to identify data issues

The data broker employees can undertake these approaches as individuals and as part of a team. For example, check *data template* and *supervisor validation* are more likely to be more *individual-centric* than *team-centric*. This flow diagram is a pattern that highlights all observed (data broker employee) approaches to identifying data issues (see Figure 5.6).

Identifying data issues is a human task (Kooper et al., 2011). So, this flow provides organisations with "a map" informing how employees identify data issues. Given each employee's skill and knowledge in handling data, this map can help identify the "pain points" where employees are sub-optimal in identifying data issues.

5.1.6.1 Theoretical Contributions

First, this study demonstrates five approaches to discovering data issues. It covers each approach and demonstrates how these five approaches are mutually exclusive and exhaustive in discovering data issues. As a result, each approach may be used to develop a theory for analysis - Theory Type 1. (Gregor, 2006, p. 622). These methodologies enable additional theorising about how organisations tackle data issues after they have been identified, such as data completeness, correctness, consistency, and availability.

Second, it conceptualises how various techniques are linked as a single flow. As a result, it opens the black box of "assess data" as one sort of workaround-centric data activities (WCDA) (Wibisono et al., 2020, 2022b, 2022c). Other data activities include compiling, transferring, retrieving, and storing data (Wibisono et al., 2022a). These data activities link and compose patterns of behaviour to solve data problems. Furthermore, it claims that finding data issues is one component of "evaluating data.". A further step known as "formulating data solution" can begin as soon as it is finished.

As a result, discovering data issues might lead to a complicated network of activities. It outlines the factors that allow each strategy to occur. So, this flow diagram represents an explanation theory - Theory Type 2 (Gregor, 2006, p. 624). This flow diagram allows for further theorising about data

consequences, such as data challenges and economic ramifications. What, for example, are the costs of these data issues? How do businesses determine these costs? How do they classify them?

5.1.6.2 Managerial Implications

According to the findings, discovering data issues is a deliberate effort. Organisations may use two or more approaches to uncover data issues (not to mention the process of fixing them). As a result, detecting and resolving data issues can be time-consuming and resource-intensive. So, organisations can train employees to combine methodologies to evaluate the data thoroughly. This expertise can also help them improve their data analysis abilities. Over time, understanding many ways can assist the organisation in addressing data issues before they arise.

5.2 Theoretical Contributions

This section describes the theoretical contributions. It explains two things. First, it summarises all identified patterns of action. Second, it shows this study's contribution to information systems research.

5.2.1 Patterns of Action Summary

After analysing all identified patterns, four features emerge: *appraise*, *negotiate*, *direct*, and *intervene* (see Table 5.5).

Appraise is to assess data thoroughly by adding a data broker. It includes two activities: identifying data issues and proposing a solution accordingly. Table 5.5 shows that all identified patterns contain an *appraise* feature. It means that the ability to assess data issues is required for all data broker and provider employees. The a*ppraise* feature connects to two other features (see Figure 5.7): *negotiate* and *direct*.

Negotiate is a joint appraisal between a data broker and a data provider. Like appraisal, it helps to identify data issues and to negotiate potential solutions. However, it requires intense collaboration between data brokers and

data providers. *Negotiate* is evident in solving *data accuracy* issues (only) (see Figure 5.7). It is understandable because data broker employees do not produce *original* data per se. So, understanding the phenomenon can be misleading without feedback from data provider employees.

Table 5.5 Summary of WCDA Patterns of Action

No	Pattern	Data Issue	Appraise	Negotiate	Direct	Intervene
1	Dual inspection	Data availability	✓			
2	Prudent control	Data availability	✓		✓	✓
3	Mindful handling	Data availability	✓			✓
4	Field inspection	Data accuracy	✓	✓	✓	
5	Fast authorisation	Data accuracy	✓			✓
6	Gold standard making	Data accuracy	✓	✓		✓

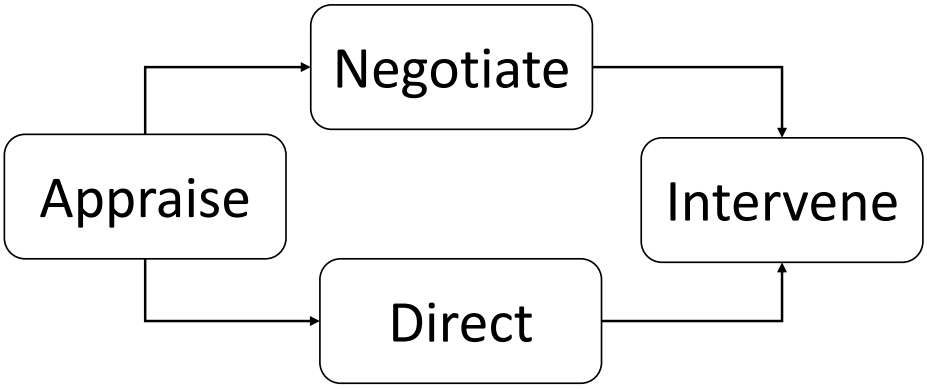

Figure 5.7 A unified pattern to fix data issues.

Direct is a command for data providers to "do something" with the data. Only a data broker can release a “direct”. It is a “guidance” to do something to resolve data issues based on data broker interpretation. It helps data providers reduce evaluation time to understand what is happening and what to do next. So, *Direct* enables data providers to intervene in data issues once the data broker employees identify them (see Figure 5.7). It guides which part of the data needs to be corrected by the provider. It also guides other actions a data provider can take – for example, retrieving data.

Intervene is a direct action to correct data and is executable for data brokers and providers. This research can see intervention as the final step to correct data issues. *Intervene* is the data provider’s and data broker’s domain (see Figure 5.7). It involves "fixing" the data content or the source where the data resides. It resolves ambiguity produced by data issues and puts in place a “better” data for future use. So, *intervene* can be viewed as the final action to correct data.

5.2.2 Contribution to Information Systems Research

This study presents several contributions to Information Systems Research, particularly for the workaround and data governance research. As presented in Table 5.8, most generated theoretical insights fall into Type II - Theory for Explanation, followed by Type 1 - Theory for Analysis (Gregor, 2006).

First, all insights challenge the conventional understanding of workaround research, which holds that a workaround is an atomic and isolated process (cf. Koppel et al., 2008; Vogelsmeier et al., 2008). This study opens the black box of workarounds and displays data activities and their connections (see Table 5.6). Also, this study differs from traditional workaround literature. Unlike workaround literature that perceives workarounds as unfavourable (because they produce data issues), this research perceives workarounds as favourable (because they fix data issues) (see Table 5.6).

Table 5.6 Positioning this work against workaround literature.

No	What to Challenge	Workaround Literature Assumption	This study
1	A workaround is a process	Atomic and Isolated	NOT Atomic – NOT Isolated (Contains linked data activities)
2	Workaround-Centric Data Activities	*Cause* data issues (negative)	*Fix* data issues (positive)

Second, Insight #3 – Insight #11 challenges a common assumption in data governance research: dealing with data issues must be a *preventive* practice (see Table 5.8). It shows that this practice can also be *curative*. Also, it is reactive, bottom-up, after data are produced (see Table 5.8). Regarding theoretical implications, a *curative* practice promotes the development of *curative-driven* data governance structures, policies, and rules. The idea of *curative-driven* data governance is *mainly* overlooked in the current data governance literature (see Table 5.7).

Table 5.7 Positioning this work against data governance literature.

No	What to Challenge	Data Governance Literature Assumption	This study
1	Data Governance View	Authority-centric	Process-centric
2	Data Governance Practice	*Preventive*	*Curative*
		Pre-determined	Reactive
		Top-down	Bottom-up
		Before data are produced	*After* data are produced

Table 5.8 Theoretical insights and contributions

No	Chapter	Section	Theoretical Insight	RQ	Theory Types in Information Systems Research (Gregor, 2006)					Literature Contribution	
					Analysis	Explanation	Prediction	Explanation & Prediction	Design & Action	Workarounds	Data Governance
1	Chapter 2	Section 2.1	*Taxonomy* of Workaround-Centric Data Issues (WCDI)	RQ1	✓					✓	
2	Chapter 2	Section 2.2	*Taxonomy* of Workaround-Centric Data Activities WCDA)	RQ2	✓					✓	
3	Chapter 3	Section 3.1	*Rules* to construct a narrative network	RQ3					✓	✓	✓
4	Chapter 4	Section 4.1	Pattern #1: Dual inspection (Data availability issues)	RQ4		✓				✓	✓
5	Chapter 4	Section 4.1	Pattern #2: Prudent control (Data availability issues)	RQ4		✓				✓	✓
6	Chapter 4	Section 4.1	Pattern #3: Mindful handling (Data availability issues)	RQ4		✓				✓	✓
7	Chapter 4	Section 4.2	Pattern #4: Field inspection (Data accuracy issues)	RQ5		✓				✓	✓
8	Chapter 4	Section 4.2	Pattern #5: Fast authorisation (Data accuracy issues)	RQ5		✓				✓	✓
9	Chapter 4	Section 4.2	Pattern #6: Gold standard making (Data accuracy issues)	RQ5		✓				✓	✓
10	Chapter 4	Section 4.3	Pattern #7: Flow to *identify* data issues	RQ6		✓				✓	✓
11	Chapter 5	Section 5.2.1	Pattern #8: Unified pattern to fix data issues	-		✓				✓	✓

Third, this study provides new insights into the literature on workarounds, namely WCDA as an organisational phenomenon. Insight #3 – Insight #10 shows how to appreciate patterns of action using the Narrative Network. This study defines seven WCDA and six patterns to address data availability and accuracy issues. So, workaround research has gained a better appreciation of WCDA and their interrelationships. This result enables researchers to identify WCDA that prior workaround research overlooked.

These contributions are insightful as this study has introduced something novel that potentially changes the *way of thinking* (Leidner, 2020) in data governance. This study shows how employees pragmatically fix data availability and data accuracy issues. Research suggests *insightfulness* (Leidner, 2020; Sparrowe & Mayer, 2011) and *novelty* (Cornelissen, 2017; Leidner, 2020; Mueller & Urbach, 2013; Sparrowe & Mayer, 2011) are two criteria for accepted theoretical contributions (Leidner, 2020).

5.3 Managerial Implications

The theoretical insights show that resolving data issues is challenging in practice. It demands a comprehensive understanding of system designs and constant monitoring of data. It also requires an endless endeavour to fix problems that lead to, or proliferate, data issues.

5.3.1 Reflection: Democratising Data Governance

This study shows how organisations **democratise their data governance**. The patterns of action reveal what operational employees do "on the ground" to deal with data issues. This research shows how employees collaborate to address data issues in an organisation. It shows that this collaboration can *potentially* reduce the learning curve of managing data - as a pattern of action. So, other employees can copy this pattern with minimal guidance from top management. Thus, it allows more employees to govern organisational data collaboratively. As this new approach to data governance is

“bottom-up” in nature, it can improve employees’ satisfaction with their working environments.

Nonetheless, democratising data governance has some limitations. They include the lack of standard methodologies for data treatment leading to privacy issues, the subjectivity of employees affecting data quality, and employees' varied knowledge and skills leading to sub-optimal data quality.

First, it may not have “standard” methodologies for *treating* data. Data collection, analysis, transfer, and evaluation rely on each employee’s mental models (see Section 4.3). As these activities can be *untested* or *experimental*, each employee can impose data leak or privacy issues for the organisation.

Second, the subjectivity of each employee determines the level of the “data quality” (see Section 4.3). An employee may have limited spatial and temporal understanding in re-capturing the facts that the data are intended to convey (see Section 4.3). So, once an employee identifies a data issue, the measure to solve it may not produce high data quality as expected.

Third, each employee’s knowledge and skills of certain data artefacts limit the data correction abilities (see Section 4.3). Some employees master sophisticated software to correct data, while others do not. So, given these facts, the “final products” of the data correction can be varied and sub-optimal. As they may be sub-optimal, they may not completely reflect the phenomenon as it occurred.

Conversely, democratising data governance solves several issues that traditional data governance fails to address. These issues encompass identifying data owners and connecting business, IT, and data management functions.

First, research indicates that *identifying* data owners is challenging for data governance (Benfeldt et al., 2019; Janssen et al., 2020). Here, the patterns of action involve “Request for Action” as a workaround-centric data activity. It is a request for intervention from a data broker to a data provider. This request allows the data provider to reflect and “do something” with the data. As a result, it enables the relevant data provider to own and manage its data. So, one can view this action as *identifying* and *strengthening data ownership*. Data

ownership is pivotal in addressing data quality issues in data governance (Redman, 1998). It makes the responsibility to control and manage data clearer.

Second, research shows that connecting "*business, IT, and data management functions*" are challenging (Zhang et al., 2022). Business units only care about their data (Fisher, 2009). They store the data in their employees' local PCs and spreadsheets (Bach, 2006). Consequently, the IT units and other departments cannot track the intended data. As such, these patterns of action enable the organisation to access these data that are "beyond the system" and transform them into different formats when needed.

Here, operational employees in the data provider can provide data based on their original business processes. Suppose there are complex "technical kinds of stuff" (e.g., data transformation, complex data analysis) with the data. These data brokers can do this on behalf of the data provider (see Fast Authorisation Pattern in Section 4.2.4.2). So, the patterns of action *reflect how organisations deal with data* in practice. That is, data have NOT been managed from the top down but from the bottom up.

Third, research shows that *data silos* are *prevalent* problems for data governance (Fisher, 2009; Zhang et al., 2022) – especially in assuring data quality (Haug et al., 2011). Multiple applications are spread throughout the organisation and are challenging to integrate. These patterns *naturally* develop a way to centralise data from multiple sources. This research finds that data broker employees collect data from multiple providers and put it in a "centralised" location (see all patterns in Chapter 4). These employees analyse the data beforehand and provide relevant reports for multiple stakeholders. Eventually, as the data are collected regularly, these employees can centralise data access and establish control over the data. They can use a data governance framework to manage these data. So, "data integration" can be achieved.

5.3.2 Recommendations For Data-Driven Organisations

The managerial implications of this research are for *data-driven organisations* that run multiple centralised and decentralised systems to support

their operations. Employees of such data-driven organisations (with multiple systems) may be naturally forced to execute WCDA for reporting tasks. This action can lead to other data activities (chained together as *patterns of action*).

This study suggests that managers can increase their awareness of WCDA. After completing this research, some analyses are made (see Table 5.9). One recommendation is to conduct regular training, promoting employees' understanding of value-chain awareness. By doing so, employees can better appreciate the data-related consequences of their workarounds for all other employees. Hence, this understanding reduces the potential negative impacts of workarounds for the organisation.

Another recommendation is that organisations remove all human actors from unnecessarily capturing data (associated with automated or non-automated processes). Instead, each organisation can utilise technical artefacts (e.g., IoT, sensors, AI) to capture data during process execution (in the field). Consequently, this study can help to improve *data accuracy* by eliminating human errors in capturing data. However, if human action for data entry is inevitable, this research suggests the organisation should enhance employees' data discipline. One strategy is to *incentivise employees to "always" enter data on time*. By doing so, organisations can avoid *data availability* issues materialising.

Furthermore, imagine a scenario where much of the organisation's data originates from other digital sources disconnected from their internal information systems. In that case, organisations must develop software intermediaries to capture data automatically. For example, they can develop an Application Programming Interface (API) to link an application to many other applications. Therefore, the data can be obtained when needed without human intervention.

Another recommendation centres on storing the data in a reliable information system (e.g., ERP) for further processing and reporting. This recommendation might improve employees' chances of avoiding WCDA. However, research suggests that poor data practice can continue even after

implementing an ERP (Drum et al., 2017), primarily if not well managed. Also, the organisation can use industrial-driven technologies such as Robotic Process Automation (RPA) or Business Process Management Systems (BPMS) to automate their processes. Hence, an organisation can improve productivity, reduce costs, minimise data errors, and save time.

Table 5.9 Recommendations for data-driven organisations

No	Recommendation	Benefit
1	Increase employees' *awareness* of WCDA – by conducting regular training	Promoting employees' understanding of value-chain awareness
		Employees *can* better appreciate the data-related consequences of their workaround actions
2	Remove all human actors from capturing data (when possible)	Improve data accuracy
3	Incentivize employees to enter data on time regularly	Improve data availability
4	Develop software intermediaries to capture data automatically	Improve data availability
5	Store all data in a well-designed 'reliable' information system	Limit WCDA occurrences
6	Train employees with sufficient domain-driven knowledge and skills.	Improve data accuracy

Finally, reconsider a situation where removing human actors is impossible. Here the organisation needs to train employees with sufficient domain knowledge and skills. Therefore, each employee can enter data correctly in the relevant systems. Even more, this understanding can help employees assess the impact of inaccurate data on other organisational

processes. It can increase their awareness of the inefficiencies produced by fixing data issues through WCDA and propagating *patterns of action*.

5.3.3 Recommendations When to Use Patterns of Action

Data issues always materialise when human actors are responsible for data capture (e.g., at the point of data creation). Therefore, employees must execute *patterns of action* to address these data issues. This study posits that although patterns are identified for specific data issues (e.g., *data availability* or *data accuracy*), they have the potential to solve other data issues. For example, when an employee is resolving data *availability* issues, the employee must also deal with the *accuracy* of the data obtained. The obtained data may not *reflect* the *phenomenon correctly* for various reasons (e.g., wrong *or* obsolete data sources). So, the employee must double-check the data before transferring the data elsewhere. In a similar vein, examining *data accuracy* issues can lead to the identification of *data consistency* issues. Data from one data source can be inconsistent with other data sources. Hence, the employee must enact specific patterns to fix these data inconsistencies.

Given these situations, Table 5.10 identifies *patterns of action* in detail and their potential usage scenarios. It shows ten scenarios an organisation can face, each containing one or more data issues.

Furthermore, these *patterns of action* are temporary solutions, as they are workarounds. An organisation must devise long-term and holistic strategies to manage these situations from re-occurring. For example, when the primary data sources are unidentified, the organisation must formalise central repositories to store data. It must assign its employees to operate and supervise these centralised repositories. Also, it needs to evaluate how its employees implement its data policies. By doing so, it may deliver a more effective data governance programme.

Table 5.10 Patterns of action by scenario

No	Scenario	Pattern of Action					
		Dual Inspection	Prudent Control	Mindful Handling	Field Inspection	Fast Authorisation	Gold Standard Creation
1	Unknown main data sources			✓	✓		
2	Multiple data versions across different sources		✓	✓			✓
3	Some employees do not give data access				✓		
4	Poor discipline in inputting accurate data				✓	✓	
5	Data providers cannot correct the data					✓	
6	The data have too many attributes to check	✓		✓			✓
7	Employees enter data into a wrong location		✓	✓	✓		
8	The data format is not consistent or is wrong					✓	
9	Poorly labelled data	✓		✓			
10	Data ownership is not clear		✓				

Organisations should train employees on data policies and procedures, set up central data repositories, and assign supervisors. This training can include regular training sessions, workshops, or even online courses to improve their knowledge and skills related to data management. Furthermore, implementing a data governance program should involve collaboration among different departments and stakeholders, including IT, legal, compliance, and business units. This strategy can help ensure that the program is comprehensive and effective in addressing the organisation's data management challenges over time.

Overall, organisations need to view data governance as a continuous process. They must regularly review and update their strategies and practices to adapt to changing circumstances and emerging technologies.

5.4 Research Limitations

There are several limitations to the study. These limitations include the focus on data brokers, the ostensive nature of the identified patterns, the inability to explain underlying mechanisms, and the ongoing process involving data providers.

First, the patterns come from data brokers, not data providers. Consequently, there is a possibility that the shape of other patterns of action could be different. This study only concentrates on data brokers and views the process through their eyes. It black boxes the process from the perspective of data providers and data receivers. Therefore, concentrating (primarily) on data brokers may prevent complicated patterns from arising. These patterns can be more challenging to analyse and theorise.

Second, these patterns reflect *ostensive* dimensions (not *performative*) (see Feldman & Pentland, 2003). Because they are *ostensive*, they may not represent each employee's actual behaviours. However, they reflect how each employee commonly understands how to perform tasks. According to research, perception is less complicated than actual behaviours (Feldman & Pentland, 2003). As a result, produced patterns of actions are parsimonious. This property is required to preserve only the most essential aspects of the phenomena (e.g., WCDA). As a result, this study can produce plausible yet straightforward theories.

Third, this study identifies many *patterns of action* to address data issues. However, it cannot thoroughly explain the underlying mechanisms that enable these patterns. These underlying mechanisms are partially tacit, distributed among participants, and sometimes embedded in the technology used (Pentland et al., 2010). Therefore, future research can investigate how these mechanisms are organised temporally and spatially to produce specific patterns of action.

Fourth, each pattern of action is part of an ongoing process to fix data issues. However, as many data activities belong to data providers, how the ongoing process finally concludes remains unclear. For example, data providers

can mindlessly execute a final data activity once the data broker has distributed the data. Therefore, producing another workaround cycle.

5.5 Future Vision: Tribalistic Data Governance as an Alternate Model for Governing Data in Organisations

This section provides a larger picture of how components in this research can facilitate future data governance research by introducing an alternate model. One component is the *patterns of actant* captured by the narrative network. This narrative network (Wibisono et al., 2020; Wibisono, Sammon, & Heavin, 2022c) captures not only *patterns of action* but also *patterns of actant* (Pentland & Feldman, 2007). Actants are human (e.g., employees) and non-human (e.g., machines) that are responsible for executing actions (Pentland & Feldman, 2007). For example, an employee (see this as an *actant*) executes *transfer data* by downloading data from SAP to a spreadsheet file. After that, the employee *analyses* the *data* in spreadsheet software.

This research demonstrates that *patterns of actant* have the potential to reveal *roles* in data governance. These roles can emerge by isolating actor relationships in the *generated* patterns of action. These *patterns of actant* reflect how these actors (e.g., employees) work. It captures nuances of work beyond formal organisational structures. Therefore, it *can* better reflect data-related roles and responsibilities.

Furthermore, workaround-centric roles are subject to change over time. Workarounds can be inherently *ad-hoc* to particular incidents (Alraddadi et al., 2018b; Li et al., 2017; Malaurent & Avison, 2016). Everyone seems to be capable of doing (virtually) everything: *retrieve* data*, transfer* data*, store* data*, evaluate* data *and request for action.* Thus, those roles are somewhat indistinguishable in the foreground. Perhaps, further research can zoom in on each data activity. In that case, it may distinguish each role from another more accurately.

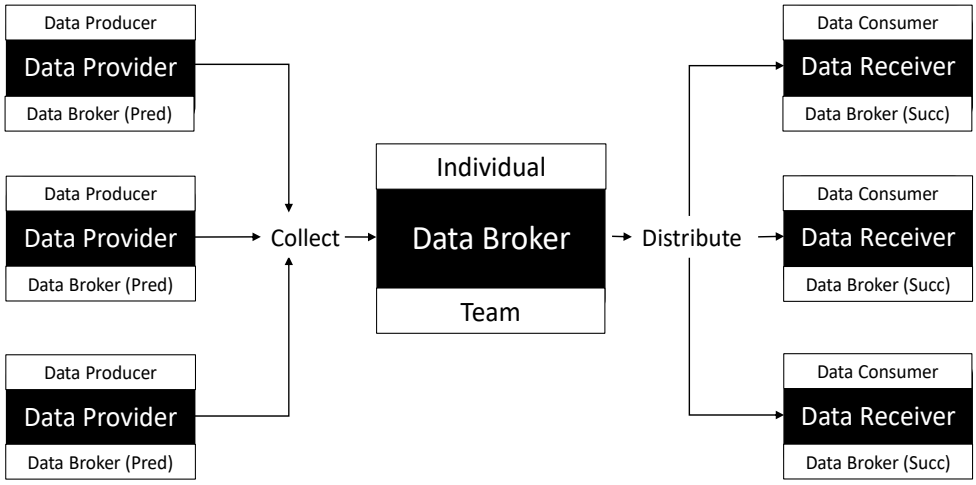

Figure 5.8 Emerging coordination structure: data brokerage.

Table 5.11 Organisational functions of the data brokerage

No	Role	Organisational Function		Can be Part of
		Collect Data	*Distribute* Data	
1	Data Broker	✓	✓	Data Provider, Data Receiver
2	Data Producer		✓	Data Provider
3	Data Consumer	✓		Data Receiver

Moreover, this study cannot plausibly infer these emerging roles for data governance (because they are dynamic over time). Nonetheless, it finds that one thing remains the same as time passes: their coordination structures (see Figure 5.8). Each coordination structure forms a "data *provider – broker – receiver*" relationship (see Figure 5.8).

This structure designates data brokers as *intermediaries* in *data management* by connecting data providers and receivers (see Figure 5.8). They work like distributors of manufactured goods (Sebastian-Coleman, 2013). They govern data in specific ways. Subsequently, they provide confidence regarding how the data can be used (Janssen & Singh, 2022). Data brokers can be individuals or units working together as a *data processing ecosystem* (Janssen

& Singh, 2022). In this context, a data broker is a "unit", not an "individual". It can manifest as both formal and informal units.

Formal means that the unit is defined by top management to address data needs. It is recognised in the organisational structure. It occurs when the organisation perceives that the task to address data needs is regular and repetitive - just like a *routine* (Feldman & Pentland, 2003).

Informal means that the unit is emergent, assembled by operational employees to support specific data needs. Informal units occur when the organisation perceives the task as unique and temporary– just like a *project* (Schwalbe, 2021).

Data brokers *collect* data from providers and distribute it to data receivers (see Table 5.11). Data providers are data suppliers. Each can be a *data producer*, which creates the data (Nagle & Sammon, 2017) or a *preceding data broker* that passes data from somewhere else (see Table 5.11). Data receivers are data customers. Each can be a *data consumer*, the end data user (Nagle & Sammon, 2017) or a *succeeding data broker* passing data elsewhere (see Table 5.11).

Data brokers have two main functions: *collecting* and *distributing* data (see Table 5.11). Data producers *distribute* data. But not to collect them. Conversely, data consumers *collect* data. But not to distribute them.

Further, the *preceding* data broker, data broker, and *succeeding* data broker indicate that data brokers can exist as a chain in an organisation. Please note that this structure can be overly complex. A data provider can be another data broker, and a data receiver can be another data broker (see Figure 5.9). Each data broker has multiple data providers. Similarly, each data broker can provide a hub for multiple data receivers. The complete structure *can* encompass *formal* and *informal* data brokers – in a single chain (see Figure 5.9).

If this study **transposes** Figure 5.8, this chain can resemble a new "organisational structure" in governing data (see Figure 5.9). Employees who work on the same "working goals" go to the same *data tribe*. They process data

that is relevant to that "tribe". They govern and manage their data with minimal interventions from top management. Hence, this research coins this concept of *tribalistic data governance.*

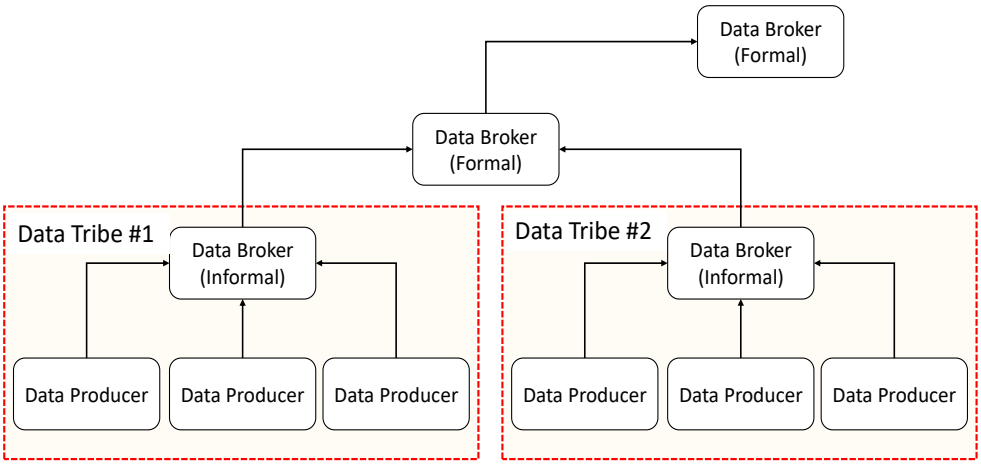

Figure 5.9 Tribalistic Data Governance – this study posits that effective data governance must start in a data tribe.

Tribalistic data governance is a *grounded design – orchestrated by employees* in the same data tribe. This study posits that a data tribe must include data producers and their immediate data brokers (see Figure 5.9).

A data tribe is an excellent locus to nurture data governance. One reason is that the data broker in this structure is entirely aware of the operational challenges of data producers. So, it is the best place to develop data governance policies, rules and data stewardship.

One reason is that some challenges can occur during traditional data governance program implementation (e.g., infrastructure breakdown or the absence of data actors). In that case, the *curative* practices help the organisation to remain agile and resilient. They re-reinterpret the rules, policies, and procedures. They act as "incident management" in governing data.

.

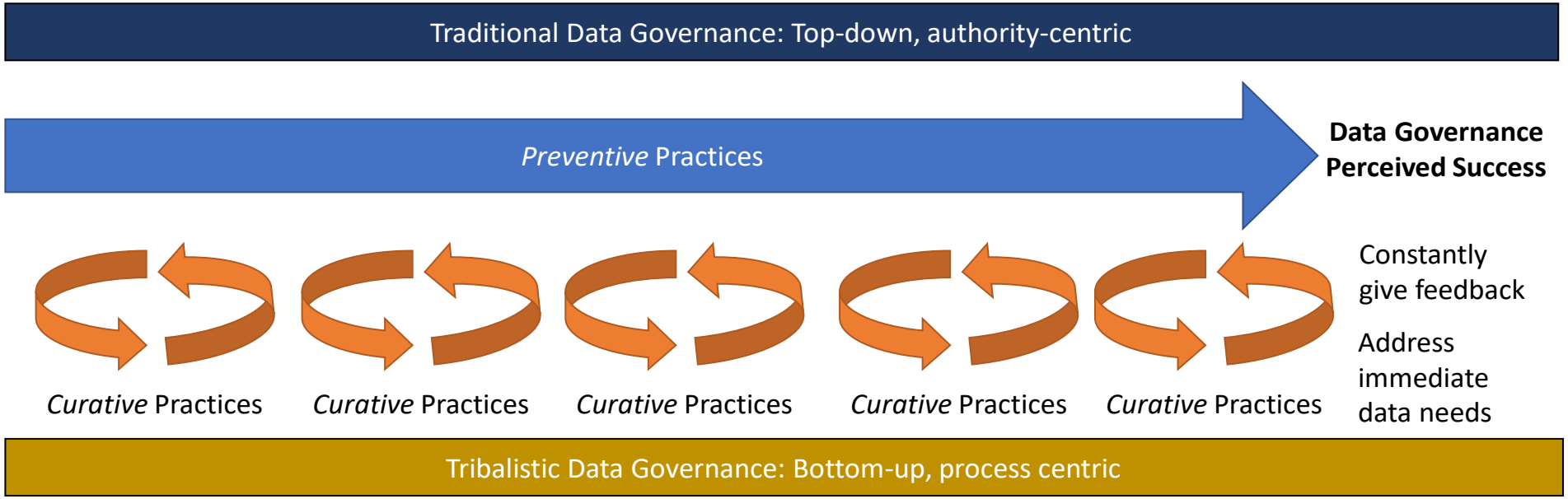

Figure 5.10. Complementing Traditional and Tribalistic Data Governance

In this situation, a data broker becomes a central liaison between the operational employees and the formal data governance organisation (e.g., Data Governance Boards and Data Stewards). It can produce helpful feedback for implementing traditional data governance over time (see Figure 5.10).

So, the data broker must constantly monitor and evaluate *curative* practices to address immediate data needs while formulating helpful feedback. The feedback encompasses *irrelevant* rules, policies and procedures imposed by the data governance office – to address operational variabilities. Also, it includes essential information that was hidden from top management. For example, data silos, metadata, used technology and data ownership.

Therefore, the organisation *can* introduce relevant and applicable data governance functions over time. With these functions, organisations can solve several barriers to deploying data governance: lack of policies, processes and defined organisational roles (Al-Ruithe et al., 2016). By doing so, organisations can improve their data governance maturities.

However, as this tribalistic concept is new, many things require further investigation. For example, how do these bottom-up structures develop policies, processes, procedures, and critical indicators? How do they complement authority-centric data governance - introduced by top management in reality? Further, how do they increase data values and minimise data-related costs and risks? How do organisations achieve consistencies and standardisations across data tribes?

These questions are challenging and require further elaboration on where workarounds manifest. Answering these questions can facilitate the emergence of a *curative*-driven data governance model. This model can complement existing data governance models that are more *preventive* (see Figure 5.10).

5.6 Further Research

Future research can examine several potential workaround and data governance research areas.

First, researchers can look at the patterns of action brought about by various data-related issues, such as data volume, data duplication, access, completeness, privacy, meaning, and leakage. What common patterns of action do these data issues cause? What patterns are unique to specific data issues? These examinations can appreciate which data issues produce the most complex patterns of action.

Second, future research can isolate similar patterns across data issues as a starting point for developing a better approach to coping with data issues and WCDA. This understanding facilitates the development of a pattern taxonomy for data issues. This taxonomy must be able to classify data-related organisations. So, it can act as a parsimonious framework to describe complex organisational forms for data governance.

Third, future research can leverage the ostensive aspects of each workaround to examine the *worldview differences* among workaround (process) actors. Researchers can compare the performative aspects to understand how context (the actual environment) shapes a workaround.

Fourth, researchers can investigate the mechanism of each pattern to influence several data governance indicators. For example, how does the pattern minimise data-related costs and risks? How does it address data privacy, accessibility, compliance, security, and ownership issues? How does it increase the value of data for the organisation? Hence, organisations can formulate improved data governance policies to deal with workarounds and data issues.

Fifth, researchers can examine other local values that *can* help to improve data quality. For example, in the Javanese context (Indonesia), there are several values, such as *tepo seliro* (toleration), *isin* (shyness), and *sungkan* (hesitations). These values may positively alleviate various data issues such as availability, credibility, protection, and security.

Sixth, future studies can develop a holistic framework for *curative* practices. It aims to support tribalistic data governance. For example, how to develop *practical* scope of *curative* practices? How to analyse *ongoing curative* practices? How to evaluate these *curative* practices? How to redesign them over time? How to transfer them to other organisational settings? And how to control & monitor them? By answering these questions, an organisation can determine conditions where tribalistic data governance can manifest effectively and efficiently. Also, they help tribalistic data governance to complement traditional data governance.

5.7 Conclusion

To conclude, data issues are everyday occurrences in organisations. They are inevitable, given operational variabilities in an organisation. Therefore, the organisation must execute WCDA *patterns of action* to fix data when a data issue is identified. By doing so, the organisation can have "quality data" to satisfy existing reporting needs. Thereafter, these quality data can be used to support organisational decision-making.

Even though these patterns of action are beneficial to *curatively* addressing data issues, the organisation must be careful. As such, the organisation must prevent patterns of action from replicating and growing uncontrollably. Thus, avoiding the emergence of *larger* hidden data factories leads to democratising data governance into constant chaos.

References

Abraham, R., Schneider, J., & vom Brocke, J. (2019). Data governance: A conceptual framework, structured review, and research agenda. *International Journal of Information Management*, *49*(July), 424–438. https://doi.org/10.1016/j.ijinfomgt.2019.07.008

Akdeniz, C. (2018). *Crash Course Data Security*. readintrobooks.com.

Al-Ruithe, M., Benkhelifa, E., & Hameed, K. (2016). A Conceptual Framework for Designing Data Governance for Cloud Computing. *Procedia Computer Science*, *94*, 160–167. https://doi.org/10.1016/j.procs.2016.08.025

Al-Ruithe, M., Benkhelifa, E., & Hameed, K. (2018). Data governance taxonomy: Cloud versus non-cloud. *Sustainability*, *10*(1). https://doi.org/10.3390/su10010095

Al-Ruithe, M., Benkhelifa, E., & Hameed, K. (2019). A systematic literature review of data governance and cloud data governance. *Personal and Ubiquitous Computing*, *23*(5–6), 839–859. https://doi.org/10.1007/s00779-017-1104-3

Alhassan, I., Sammon, D., & Daly, M. (2018). Data governance activities: a comparison between scientific and practice-oriented literature. *Journal of Enterprise Information Management*, *31*(2), 300–316. https://doi.org/10.1108/JEIM-01-2017-0007

Allen, I., & Allen, S. (2016). God Terms and Activity Systems: A Definition of Religion for Political Science. *Political Research Quarterly*, *69*(3), 557–570. https://doi.org/10.1177/1065912916654014

Alraddadi, A., Champion, D., & Lagna, A. (2018a). Exploring Institutionalization of Workarounds: The Case of ERP Implementation in Saudi Arabian SMEs. *Thirty Ninth International Conference on Information Systems, San Francisco 2018*. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1137&context=icis2018

Alraddadi, A., Champion, D., & Lagna, A. (2018b). The Role of Workarounds in Benefits Realisation: Evidence from a Field Study in Saudi Arabia. *UK Academy for Information Systems Conference Proceedings*, *2*. https://aisel.aisnet.org/ukais2018/2

Altendeitering, M., & Guggenberger, T. M. (2021). Designing Data Quality Tools: Findings from an Action Design Research Project at Boehringer Ingelheim. *Twenty-Ninth European Conference on Information Systems*, *Ecis*, 1–16. https://aisel.aisnet.org/ecis2021_rp/95

Altendeitering, M., & Tomczyk, M. (2022). A Functional Taxonomy of Data Quality Tools: Insights from Science and Practice. *Wirtschaftsinformatik 2022 Proceedings*, *February*.

https://aisel.aisnet.org/wi2022/business_analytics/business_analytics/4

Alter, S. (2014). Theory of Workarounds. *Communications of the Association for Information Systems*, *34*(March), 1041–1066.

Alvesson, M., & Sandberg, J. (2011). Generating Research Questions through Problematization. *Academy of Management Review*, *36*(2), 247–271. https://www-jstor-org.libezproxy.open.ac.uk/stable/pdf/41318000.pdf?refreqid=excelsior%3A6fbc0ddf365a66bdceded563c806e0ff

Assis-Hassid, S., Grosz, B. J., Zimlichman, E., Rozenblum, R., & Bates, D. W. (2019). Assessing EHR use during hospital morning rounds: A multi-faceted study. *PLoS ONE*, *14*(2), 1–16. https://doi.org/10.1371/journal.pone.0212816

Attai, L. J. (2018). *Student Data Privacy: Building a School Compliance Program*. Rowman & Littlefield Publishers.

Azad, B., & King, N. (2012). Institutionalized computer workaround practices in a Mediterranean country: An examination of two organizations. *European Journal of Information Systems*, *21*(4), 358–372. https://doi.org/10.1057/ejis.2011.48

Bach, P. (2006). *A 360-Degree Approach to Data*.

Baird, A. (2021). On writing research articles well: A guide for writing is papers. *Journal of the Association for Information Systems*, *22*(5), 1197–1211. https://doi.org/10.17705/1jais.00711

Barrett, A. K. (2018). Technological appropriations as workarounds: Integrating electronic health records and adaptive structuration theory research. *Information Technology and People*, *31*(2), 368–387. https://doi.org/10.1108/ITP-01-2016-0023

Baskarada, S. (2014). Qualitative Research : Case Study Guidelines. *The Qualitative Report*, *19*, 1–2.

Batini, C., Cappiello, C., Francalanci, C., & Maurino, A. (2009). Methodologies for data quality assessment and improvement. *ACM Computing Surveys*, *41*(3). https://doi.org/10.1145/1541880.1541883

Baysari, M. T., Hardie, R., Lake, R., Richardson, L., Mccullagh, C., Gardo, A., & Westbrook, J. (2018). Longitudinal study of user experiences of a CPOE system in a pediatric hospital. *International Journal of Medical Informatics*, *109*(August 2017), 5–14. https://doi.org/10.1016/j.ijmedinf.2017.10.018

Becker, M. (2007). Information governance in NHS's NPfIT: A case for policy specification. *International Journal of Medical Informatics*, *76*(5–6), 432–437. https://doi.org/10.1016/j.ijmedinf.2006.09.008

Beerepoot, I., & van de Weerd, I. (2018). Prevent, redesign, adopt or ignore: improving

healthcare using knowledge of workarounds. *Twenty-Sixth European Conference on Information Systems*. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1119&context=ecis2018_rp

Behrens, S. (2009). Shadow systems : The good, the bad and the ugly. *Communication of the ACM*, *52*(2), 124–129.

Benbasat, I., & Zmud, R. W. (1999). Empirical research in information systems: The practice of relevance. *MIS Quarterly*, *23*(1), 3–16. https://doi.org/10.2307/249403

Benfeldt, O., Persson, J. S., & Madsen, S. (2019). Data Governance as a Collective Action Problem. *Information Systems Frontiers*, *22*, 299–313. https://doi.org/10.1007/s10796-019-09923-z

Berson, A., & Dubov, L. (2011). *Master Data Management and Data Governance, Second Edition*. McGraw-Hill/Osborne. https://books.google.co.id/books?id=SnS8wgEACAAJ

Bhimani, A., & Bromwich, M. (2009). *Management Accounting: Retrospect and Prospect*. CIMA Publishing.

Blijleven, V., Koelemeijer, K., & Jaspers, M. (2019). SEWA: A framework for sociotechnical analysis of electronic health record system workarounds. *International Journal of Medical Informatics*, *125*(May 2018), 71–78. https://doi.org/10.1016/j.ijmedinf.2019.02.012

Böhm, A., Glaser, B., & Strauss, A. (2004). Theoretical Coding: Text Analysis in Grounded Theory. *A Companion to Qualitative Research*, *January 2004*, 270–275.

Born, F., & Krönung, J. (2016). Deviant cloud usage in public institutions - A matter of personal innovativeness? *Twenty-Fourth European Conference on Information Systems (ECIS)*. http://aisel.aisnet.org/ecis2016_rip%0Ahttp://aisel.aisnet.org/ecis2016_rip/19

Bowen, J. R. (1986). On the Political Construction of Tradition: Gotong Royong in Indonesia. *The Journal of Asian Studies*, *45*(3), 545–561. https://doi.org/10.2307/2056530

Bozan, K., & Berger, A. (2018). The effect of unmet expectations of information quality on post-acceptance workarounds among healthcare providers. *Proceedings of the 51st Hawaii International Conference on System Sciences*, *9*, 3039–3048. http://engagement.hicss.org:81/papers/0385/paper0385.pdf

Brooks, J., Ravishankar, M. N., & Ilan Oshri. (2015). Regulating vendor-client workarounds : An information brokering approach. *Thirty Sixth International Conference on Information Systems*, 1–10.

Bryman, A. (2012). *Social Research Methods 4th Edition* (2012th ed.). Oxford

University Press.

Burns, A. ., Young, J., Courtney, J. F., Roberts, T., & Ellis, T. S. (2015). Exploring the Role of Contextual Integrity in Electronic Medical Record (EMR) System Workaround Decisions: An Information Security and Privacy Perspective. *AIS Transactions on Human-Computer Interaction*, *7*(3), 142–165.

Cameron, K. S., & Quinn, R. E. (1988). Organizational paradox and transformation. In *Paradox and transformation: Toward a theory of change in organization and management.* (pp. 1–18). Ballinger Publishing Co/Harper & Row Publishers.

Carruthers, C., & Jackson, P. (2018). *The Chief Data Officer's Playbook*. Facet Publishing.

Caulkins, J. P., Morrison, E. L., & Weidemann, T. (2007). Spreadsheet errors and decision making: Evidence from field interviews. *Journal of Organizational and End User Computing*, *19*(3), 1–23. https://doi.org/10.4018/joeuc.2007070101

Chatterjee, S., & Davison, R. M. (2021). The need for compelling problematisation in research: The prevalence of the gap-spotting approach and its limitations. *Information Systems Journal*, *31*(2), 227–230. https://doi.org/10.1111/isj.12316

Cheong, L. K., & Chang, V. (2007). The need for data governance: A case study. *ACIS 2007 Proceedings - 18th Australasian Conference on Information Systems*, 999–1008.

Chua, C. E. H., Storey, V. C., & Chen, L. (2014). Central IT or Shadow IT? Factors shaping user's decision to go rogue with IT. *Thirty Fifth International Conference on Information Systems*, 1–14.

Collins, E. F. (2004). Islam and the Habits of Democracy: Islamic Organizations in Post-New Order South Sumatra. In *Indonesia* (Vol. 78). Cornell University Press. https://www.jstor.org/stable/3351289

Corbin, J. M., & Strauss, A. L. (1990). Grounded theory research: Procedures, canons, and evaluative criteria. *Qualitative Sociology*, *13*(1), 3–21. https://doi.org/10.1007/BF00988593

Cornelissen, J. (2017). Editor's Comments : Developing Propositions, a Process Model, or a Typology? Addressing the Challenges of Writing Theory Without Boilerplate. *Academy of Management Review*, *42*(1), 1–9.

Courtright, J. F., Acton, W. H., Frazier, M. L., & Lane, J. W. (1998). Effects of "workarounds" on perceptions of problem importance during operational test. *Proceeding of the Human Factors Society -32nd Annual Meeting*, 1150–1153. https://doi.org/https://doi.org/10.1177/154193128803201705

D'Adderio, L. (2011). Artifacts at the centre of routines : performing the material turn in routines theory. *Journal of Institutional Economics*, *7*(2), 197–230. https://doi.org/10.1017/S174413741000024X

Daneshkohan, A., Alimoradi, M., Ahmadi, M., & Alipour, J. (2022). Data quality and data use in primary health care: A case study from Iran. *Informatics in Medicine Unlocked*, *28*, 100855. https://doi.org/10.1016/j.imu.2022.100855

Danilova, K. B. (2019). Process owners in business process management: a systematic literature review. *Business Process Management Journal*, *25*(6), 1377–1412. https://doi.org/10.1108/BPMJ-05-2017-0123

Das, K., Gryseels, M., Sudhir, P., & Tee Kan, K. (2016). *Unlocking Indonesia's digital opportunity*.

Davison, R. M., & Díaz Andrade, A. (2018). Promoting indigenous theory. *Information Systems Journal*, *28*(5), 759–764. https://doi.org/10.1111/isj.12203

Davison, R. M., & Ou, C. X. J. J. (2018). Subverting organizational IS policy with feral systems: a case in China. *Industrial Management and Data Systems*, *118*(3), 570–588. https://doi.org/10.1108/IMDS-04-2017-0153

Davison, R. M., Wong, L. H. M. M., Alter, S., & Ou, C. X. J. (2019). Adopted Globally But Unusable Locally : What Workarounds Reveal About Adoption , Resistance , Compliance and Non-Compliance. *Twenty-Seventh European Conference on Information Systems (ECIS2019)*, 0–16.

Denzin, N. K. (1978). *The Research Act: A Theoretical Introduction to Sociological Methods Second Edition*. McGraw-Hill, Inc. http://library1.nida.ac.th/termpaper6/sd/2554/19755.pdf

Djalali, S., Ursprung, N., Rosemann, T., Senn, O., & Tandjung, R. (2015). Undirected health IT implementation in ambulatory care favors paper-based workarounds and limits health data exchange. *International Journal of Medical Informatics*, *84*(11), 920–932. https://doi.org/10.1016/j.ijmedinf.2015.08.001

Drum, D., Pernsteiner, A., & Revak, A. (2016). Walking a mile in their shoes: user workarounds in a SAP environment. *International Journal of Accounting & Information Management*, *24*(2), 185–204.

Drum, D., Pernsteiner, A., & Revak, A. (2017). Workarounds in an SAP environment: Impacts on accounting information quality. *Journal of Accounting and Organizational Change*, *13*(1), 44–64. https://doi.org/10.1108/JAOC-05-2015-0040

Drum, D., Standifer, R., & Bourne, K. (2015). Facing the Consequences: Examining a Workaround Outcomes-Based Model. *Journal of Information Systems*. https://doi.org/10.2308/isys-50875

Dunford, B. B., Lafayette, W., & Perrigino, M. B. (2017). The Organization Made Us Do it: Demanding Formalization and Workaround Attributions. *Academy of Management Proceeding*.

Dunford, B. B., & Perrigino, M. B. (2018). The social construction of workarounds.

Advances in Industrial and Labor Relations, *24*, 7–28. https://doi.org/10.1108/S0742-618620180000024003

Eikey, E. V, Murphy, Alison, R., Reddy, M. C., & Xu, H. (2015). Designing for privacy management in hospitals: Understanding the gap between user activities and IT staff's understandings. *International Journal of Medical Informatics*, *84*(12), 1065–1075. https://doi.org/10.1016/j.ijmedinf.2015.09.006

Eisenhardt, K. M. (1989). Building Theories from Case Study Research. *Academy of Management Review*, *14*(4), 532–550. https://www.jstor.org/stable/pdf/258557.pd

Eisenhardt, K. M. (2021). What is the Eisenhardt Method, really? *Strategic Organization*, *19*(1), 147–160. https://doi.org/10.1177/1476127020982866

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory Building from Cases : Opportunities and Challenges. *Academy of Management Journal*, *50*(1), 25–32. https://doi.org/10.1177/0170840613495019

Ejnefjäll, T., & Ågerfalk, P. J. (2019). Conceptualizing workarounds: Meanings and manifestations in information systems research. *Communications of the Association for Information Systems*, *45*(1), 340–363. https://doi.org/10.17705/1CAIS.04520

Ellingsen, G., Monteiro, E., & Røed, K. (2012). Integration as interdependent workaround. *International Journal of Medical Informatics*, *82*(5), e161–e169. https://doi.org/10.1016/j.ijmedinf.2012.09.004

Emeka-Nwokeji. (2012). Repositioning Accounting Information System Through Effective Data Quality Management: A Framework For Reducing Costs And Improving Performance. *International Journal of Scientific & Technology Research*, *1*(10), 86–95.

Feldman, M. (2016). Routines as Process - Past, Present, and Future. In *Organizational Routines: How They Are Created, Maintained, and Changed*. Oxford Scholarship. https://doi.org/10.1093/acprof

Feldman, M., & Almquist, J. (2012). Analyzing the Implicit in Stories. In J. A. Holstein & J. F. Gubrium (Eds.), *Varieties of Narrative Analysis* (pp. 207–228). SAGE Publications, Inc. https://doi.org/10.4135/9781506335117

Feldman, M., & Pentland, B. T. (2003). Reconceptualizing Organizational Routines as a Source of Flexibility and Change. *Administrative Science Quarterly*, *48*(1), 94–118. https://www.docme.ru/doc/2197752/978-3-319-62235-4

Feldman, M., & Pentland, B. T. (2008). Issues in Empirical Field Studies or Organizational Routines. In M. C. Becker (Ed.), *Handbook of Organizational Routines* (pp. 1–31). Edward Elgar Publishing. https://doi.org/https://doi.org/10.4337/9781848442702.00021

Finney, S., & Corbett, M. (2007). ERP implementation: A compilation and analysis of critical success factors. *Business Process Management Journal*, *13*(3), 329–347. https://doi.org/10.1108/14637150710752272

Fisher, T. (2009). *The Data Asset: How Smart Companies Govern Their Data for Business Success*. Wiley. https://www.wiley.com/en-ca/The+Data+Asset%3A+How+Smart+Companies+Govern+Their+Data+for+Business+Success+-p-9780470508008

Flanagan, M. E., Saleem, J. J., Millitello, L. G., Russ, A. L., & Doebbeling, B. N. (2013). Paper- and computer-based workarounds to electronic health record use at three benchmark institutions. *Journal of the American Medical Informatics Association*, *20*(E1), 59–66. https://doi.org/10.1136/amiajnl-2012-000982

Foss, S. K., & Waters, W. J. C. (2007). *Destination dissertation : a traveler's guide to a done dissertation*. Rowman & Littlefield Publishers.

Fries, V., Wiesche, M., & Krcmar, H. (2016). The Dualism of Workarounds: Effects of Technology and Mental Workload on Improvement and Noncompliant Behavior within Organizations. *Thirty Seventh International Conference on Information Systems*, 1–13.

Fürstenau, D., & Rothe, H. (2014). Shadow It Systems: Discerning the Good and the Evil. *Twenty Second European European Conference on Information Systems*, 0–14. http://aisel.aisnet.org/ecis2014%0Ahttp://aisel.aisnet.org/ecis2014/proceedings/track15/9%0Ahttp://aisel.aisnet.org/ecis2014%0Ahttp://aisel.aisnet.org/ecis2014/proceedings/track15/9

Fürstenau, D., Rothe, H., & Sandner, M. (2021). Leaving the Shadow: A Configurational Approach to Explain Post-identification Outcomes of Shadow IT Systems. *Business and Information Systems Engineering*, *63*(2), 97–111. https://doi.org/10.1007/s12599-020-00635-2

Furstenau, D., & Sandner, M. (2017). Shadow IT, risk, and shifting power relations in organizations. *Communications of the Association for Information Systems*, *41*(1). https://doi.org/https://doi.org/10.17705/1CAIS.04103

Fürstenau, D., Sandner, M., & Anapliotis, D. (2016). Why Do Shadow Systems Fail? An Expert Study on Determinants of Discontinuation. *Twenty-Fourth European Conference on Information Systems*, 1–16.

Garg, V. K. (2007). *Wireless communications and networking*. Elsevier Morgan Kaufmann.

Glaser, B., & Strauss, A. (1967). The Discovery of Grounded Theory: Strategies for Qualitative Research. In *BMC Public Health* (Vol. 5, Issue 1). Sociology Press. https://ejournal.poltektegal.ac.id/index.php/siklus/article/view/298%0Ahttp://repositorio.unan.edu.ni/2986/1/5624.pdf%0Ahttp://dx.doi.org/10.1016/j.jana.201

5.10.005%0Ahttp://www.biomedcentral.com/1471-2458/12/58%0Ahttp://ovidsp.ovid.com/ovidweb.cgi?T=JS&P

Goff, M., Hodgson, D., Bailey, S., Bresnen, M., Elvey, R., & Checkland, K. (2021). Ambiguous workarounds in policy piloting in the NHS: Tensions, trade-offs and legacies of organisational change projects. *New Technology, Work and Employment*, 1–27. https://doi.org/10.1111/ntwe.12190

Goldkuhl, G. (2012). Pragmatism vs interpretivism in qualitative information systems research. *European Journal of Information Systems*, *21*(2), 135–146. https://doi.org/10.1057/ejis.2011.54

Goode, S., & Gregor, S. (2009). Rethinking organisational size in IS research: Meaning, measurement and redevelopment. *European Journal of Information Systems*, *18*(1), 4–25. https://doi.org/10.1057/ejis.2009.2

Gordon, P. (2019). *Data Leakage - Threats and Mitigation*. SANS Institute - Information Security Reading Room.

Gozman, D., & Willcocks, L. (2015). Crocodiles in the Regulatory Swamp : Navigating the Dangers of Outsourcing , SaaS and Shadow IT. *Thirty Sixth International Conference on Information Systems*, 1–20. https://doi.org/10.1088/1755-1315/155/1/012011

Grahlmann, K. R., Helms, R. W., Hilhorst, C., Brinkkemper, S., & Van Amerongen, S. (2012). Reviewing Enterprise Content Management: A functional framework. *European Journal of Information Systems*, *21*(3), 268–286. https://doi.org/10.1057/ejis.2011.41

Gregor, S. (2006). The nature of theory in Information Systems. *MIS Quarterly*, *30*(3), 611–642. https://aisel.aisnet.org/misq/vol30/iss3/5/

Gregor, S., & Klein, G. (2014). Eight obstacles to overcome in the theory testing genre. *Journal of the Association for Information Systems*, *15*(11), i–xix. https://doi.org/10.17705/1jais.00382

Guerreiro, S. (2021). Conceptualizing on Dynamically Stable Business Processes Operation : A Literature Review on Existing Concepts. *Business Process Management Journal*, *27*(1), 24–54. https://doi.org/10.1108/BPMJ-02-2020-0072

Györy, A., Cleven, A., Uebernickel, F., & Brenner, W. (2012). Exploring the shadows: IT governance approaches to user-driven innovation. *European Conference on Information Systems*, 1–13. https://doi.org/10.3354/dao02225

Haag, S., & Eckhardt, A. (2014). Sensitizing Employees ' Corporate IS Security Risk Perception. *Thirty Fifth International Conference on Information Systems,* 1–17.

Haag, S., Eckhardt, A., & Bozoyan, C. (2015). Are shadow system users the better is users? – Insights of a lab experiment. *Thirty Sixth International Conference on*

Information Systems, 1–20. https://aisel.aisnet.org/icis2015/proceedings/ITimplementation/16/

Haag, S., Eckhardt, A., & Schwarz, A. (2018). The acceptance of justifications among shadow it users and nonusers – An empirical analysis. *Information & Management*, *56*(November), 731–741. https://doi.org/10.1016/J.IM.2018.11.006

Hammond, M. (2018). 'An interesting paper but not sufficiently theoretical': What does theorising in social research look like? *Methodological Innovations*, *11*(2), 205979911878775. https://doi.org/10.1177/2059799118787756

Hansen, D. R., & Mowen, M. M. (2018). *Cornerstones of Managerial Accounting* (7th ed.). Cengage Learning.

Hansen, & Schaltegger, S. (2016). The sustainability balanced scorecard: A systematic review of architectures. *Journal of Business Ethics*, *133*(2), 193–221. https://doi.org/10.1007/s10551-014-2365-1

Hassan, N. R., & Willcocks, L. P. (2021). Introduction: Why Theory? (Mis)Understanding the Context and Rationale. In N. R. Hassan & L. P. Willcocks (Eds.), *Advancing Information Systems Theories* (pp. 1–52). Palgrave Macmillan Ltd. https://doi.org/10.1007/978-3-030-64884-8_1

Haug, A., Zachariassen, F., & van Liempd, D. (2011). The costs of poor data quality. *Journal of Industrial Engineering and Management*, *4*(2), 168–193. https://doi.org/10.3926/jiem.2011.v4n2.p168-193

Hayes, G. R., Lee, C. P., & Dourish, P. (2011). Organizational Routines, Innovation, and Flexibility: The Application of Narrative Networks to Dynamic Workflow. *International Journal of Medical Informatics*, *80*(8), e161–e177. https://doi.org/10.1016/j.ijmedinf.2011.01.005

Hermawan, M. S., & Loo, M. K. (2019). The Construction of Kekeluargaan as an Indonesia's Organizational Culture. *Jurnal Humaniora*, *31*(1), 1. https://doi.org/10.22146/jh.v31i1.42851

Holton, J. A. (2012). The Coding Process and Its Challenges. *The SAGE Handbook of Grounded Theory*, *9*(1), 265–289. https://doi.org/10.4135/9781848607941.n13

Horngren, C. T., Datar, S. M., Rajan, M. V, & Ittner, C. D. (2018). *Cost Accounting: A Managerial Emphasis* (16th ed.). Pearson.

Hu, Z. (2000). A XML Server Architecture Based on Presentation-Abstraction-Control Style. *OOIS 2000 : 6th International Conference on Object Oriented Information Systems 18-20 December 2000, London, UK Proceedings*, 469.

Huber, M., Zimmermann, S., Rentrop, C., & Felden, C. (2018). Toward a Conceptual Decision Framework for Shadow IT Integration. *Twenty-Fourth Americas Conference on Information Systems*, 1–5.

Huuskonen, S., & Vakkari, P. (2013). I Did It My Way: Social workers as secondary designers of a client information system. *Information Processing and Management*, *49*(1), 380–391. https://doi.org/10.1016/j.ipm.2012.05.003

Ibrahim, S., Donelle, L., Regan, S., & Sidani, S. (2019). A Qualitative Content Analysis of Nurses' Comfort and Employment of Workarounds With Electronic Documentation Systems in Home Care Practice. *Canadian Journal of Nursing Research*, *52*(1), 084456211985550. https://doi.org/10.1177/0844562119855509

Ignatiadis, I., & Nandhakumar, J. (2009). The Effect of ERP System Workarounds on Organizational Control: An interpretivist case study. *Scandinavian Journal of Information Systems*, *21*(2), 59–90. http://aisel.aisnet.org/sjis/vol21/iss2/3

Ilie, V. (2013). Psychological reactance and user workarounds. A study in the context of electronic medical records implementations. *Twenty First European Conference on Information Systems (ECIS)*, *2013*, 1–7. http://www.staff.science.uu.nl/~vlaan107/ecis/files/ECIS2013-0816-paper.pdf

Irawanto, D. W. (2018). Conformity : the lock- in effect of social ties Introduction : group identity and the ambivalence. In A. Ledeneva, A. Bailey, S. Barron, C. Curro, & E. Teague (Eds.), *Global Encyclopaedia of Informality* (Vol. 1). UCL Press. https://doi.org/https://doi.org/10.2307/j.ctt20krxh9.13

Iversen, J., & Mathiassen, L. (2000). Lessons from implementing a software metrics program. *Proceedings of the Annual Hawaii International Conference on System Sciences*, *2000-Janua*(c), 1–11.

Jagannath, S., Sarcevic, A., & Forte, A. (2018). "We Are Not Entirely Replacing Paper": Understanding Paper Persistence in Emergency Medical Settings. *Conference on Computer Supported Cooperative Work and Social Computing*, 249–252. https://doi.org/10.1145/3272973.3274067

Jagannath, S., Sarcevic, A., Young, V., & Myers, S. (2019). Temporal Rhythms and Patterns of Electronic Documentation in Time-Critical Medical Work. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–13. https://doi.org/10.1145/3290605.3300564

Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. *Government Information Quarterly*, *37*(3), 101493. https://doi.org/10.1016/j.giq.2020.101493

Janssen, & Singh, J. (2022). Data intermediary. *Internet Policy Review*, *11*(1), 1–9. https://doi.org/https://doi.org/10.14763/2022.1.1644 Published:

Johnston, T. (2014). *Bitemporal Data: Theory and Practice*.

Kahane, R. (1984). Hypotheses on Patronage and Social Change: A Comparative

Perspective. *Ethnology*, *23*(1), 13. https://doi.org/10.2307/3773390

Kaplan, R. S., & Norton, D. P. (1996). *The Balanced Scorecard: Translating Strategy into Action*. Harvard Business Press.

Khalil, S., Winkler, T. J., & Xiao, X. (2017). Two Tales of Technology: Business and IT Managers ' Technological Frames Related to Cloud Computing. *Thirty Eighth International Conference on Information Systems*, 0–20.

Khatri, V., & Brown, C. V. (2010). Designing data governance. *Communications of the ACM*, *53*(1), 148. https://doi.org/10.1145/1629175.1629210

Klein, G., Jiang, J., & Saunders, C. (2006). Leading the Horse to Water. *Communications of the Association for Information Systems*, *18*. https://doi.org/10.17705/1cais.01813

Kline, R. B. (2019). *Becoming a behavioral science researcher : a guide to producing research that matters* (2nd ed.).

Koltay, T. (2016). Data governance, data literacy and the management of data quality. *IFLA Journal*, *42*(4), 303–312. https://doi.org/10.1177/0340035216672238

Kooper, M. N., Maes, R., & Lindgreen, E. E. O. R. (2011). On the governance of information: Introducing a new concept of governance to support the management of information. *International Journal of Information Management*, *31*(3), 195–200. https://doi.org/10.1016/j.ijinfomgt.2010.05.009

Koppel, R., Smith, S., Blythe, J., & Kothari, V. (2015). Workarounds to Computer Access in Healthcare Organizations: You Want My Password or a Dead Patient? *Studies in Health Technology and Informatics*, *208*, 215–220. https://doi.org/10.3233/978-1-61499-488-6-215

Koppel, R., Wetterneck, T., Telles, J. L., & Karsh, B.-T. (2008). Workarounds to Barcode Medication Administration Systems: Their Occurrences, Causes, and Threat to Patient Safety. *Journal of America Medical Informatics*, *15*(4), 408–423. https://doi.org/10.1197/jamia.M2616.Introduction

Kopper, A., Furstenau, D., Zimmermann, S., Rentrop, C., Rothe, H., Strahringer, S., & Westner, M. (2018). Business-Managed IT: A Conceptual Framework and Empirical Illustration. *Twenty-Sixth European Conference on Information Systems*. http://ecis2018.eu/wp-content/uploads/2018/09/1447-doc.pdf

Kosanke, K., Vernadat, F., & Zelm, M. (1999). CIMOSA: Enterprise engineering and integration. *Computers in Industry*, *40*(2), 83–97. https://doi.org/10.1016/S0166-3615(99)00016-0

Ladley, J. (2020). *Data Governance: How to Design, Deploy, and Sustain an Effective Data Governance Program*. Academic Press, Elsevier. https://doi.org/10.1017/CBO9781107415324.004

Lalley, C., & Malloch, K. (2010). Workarounds: The hidden pathway to excellence. *Nurse Leader*, *8*(4), 29–32. https://doi.org/10.1016/j.mnl.2010.05.009

Laney, D. B. (2018). *Infonomics: How to Monetize, Manage, and Measure Information as an Asset for Competitive Advantage*. Bibliomotion, Inc.

Langley, A. (1999). Strategies for Theorizing from Process Data. *The Academy of Management Review*, *24*(4), 691–710. http://www.jstor.org/stable/259349

Leidner, D. E. (2020). What's in a contribution. *Journal of the Association for Information Systems*, *21*(1), 238–245. https://doi.org/10.17705/1jais.00598

Lepeniotis, P. (2020). *Part 2: The cost of Poor Data Quality*. Data Clarity Limited. https://www.linkedin.com/pulse/part-2-cost-poor-data-quality-dr-pana-lepeniotis/

Li, Y., Haake, P., & Mueller, B. (2017). Explaining the influence of workarounds on effective use -The case of a supply chain management system. *Proceedings of the 25th European Conference on Information Systems (ECIS)*.

Lovett, L., Holden, R. J., Anders, S. H., Hong, J. Y., & Karsh, B. (2013). Using a sociotechnical framework to understand adaptations in health IT implementation. *International Journal of Medical Informatics*, *82*(12), e331–e344. https://doi.org/10.1016/j.ijmedinf.2013.01.009

Lüker, N., Winkler, T. J., & Kude, T. (2016). IT Consumerization and Compliant Use : Do Policies Matter? *Pacific Asia Conference on Information Systems, PACIS 2016 - Proceedings*. https://aisel.aisnet.org/pacis2016/

Magnis-Suseno, F. (1984). Etika Jawa Sebuah Analisa Falsafi tentang Kebijaksanaan Hidup Orang Jawa. In *PT Gramedia Pustaka Utama* (Vol. 3, Issue 2, pp. 124–136). http://puslit2.petra.ac.id/ejournal/index.php/int/article/view/16388

Magnis-Suseno, F. (1997). *Javanese ethics and world-view: The Javanese idea of the good life*. Gramedia Pustaka Utama.

Maitlis, S., & Christianson, M. (2014). Sensemaking in Organizations : Taking Stock and Moving Forward. *The Academy of Management Annals*, *8*(1), 57–125. https://doi.org/10.1080/19416520.2014.873177

Malaurent, J., & Avison, D. (2011). ERP global template and organizational informal structures a practice-based study. *European Conference on Information Systems (ECIS)*. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85011046984&partnerID=40&md5=6b4a20bc18b62121a6c82707b6db9871 NS -

Malaurent, J., & Avison, D. (2016). Reconciling global and local needs: A canonical action research project to deal with workarounds. *Information Systems Journal*, *26*(3), 227–257. https://doi.org/10.1111/isj.12074

Mallmann, G. L., Carlos, A., Maçada, G., Oliveira, M., Maçada, A. C. G., & Oliveira, M. (2018). The influence of shadow IT usage on knowledge sharing: An exploratory study with IT users. *Business Information Review*, *35*(1), 17–28. https://doi.org/10.1177/0266382118760143

Mallmann, G. L., Maçada, A. C. G., & Eckhardt, A. (2018). We are social: A social influence perspective to investigate shadow IT usage. *Twenty-Sixth European Conference on Information Systems (ECIS2018)*. http://ecis2018.eu/wp-content/uploads/2018/09/2115-doc.pdf

Manga, J., & Xiao, N. (2020). Physicians' perceived threats and electronic medical record workaround. *26th Americas Conference on Information Systems, AMCIS 2020*, 0–5.

McClelland, S. I., Petrides, L. A., & Nodine, T. R. (2004). Costs and benefits of the workaround: inventive solution or costly alternative. *International Journal of Educational Management*, *18*(2), 100–108. https://doi.org/10.1108/09513540410522234

Mendling, J., Berente, N., Seidel, S., & Grisold, T. (2021). The Philosopher's Corner: Pluralism and Pragmatism in the Information Systems Field: The Case of Research on Business Processes and Organizational Routines. *Data Base for Advances in Information Systems*, *52*(2), 127–140. https://doi.org/10.1145/3462766.3462773

Merkus, J., Helms, R. W., & Kusters, R. (2019). Data Governance and Information Governance: set of definitions in relation to Data and Information as part of DIKW. *Proceedings of the 21st International Conference on Enterprise Information Systems*, *May*.

Merschbrock, C., & Figueres-Munoz, A. (2015). Circumventing Obstacles in Digital Construction Design – A Workaround Theory Perspective. *Procedia Economics and Finance*, *21*(2212), 247–255. https://doi.org/10.1016/S2212-5671(15)00174-4

Moeini, M., Rahrovani, Y., & Chan, Y. E. (2019). A review of the practical relevance of IS strategy scholarly research. *Journal of Strategic Information Systems*, *28*(2), 196–217. https://doi.org/10.1016/j.jsis.2018.12.003

Morrison, B. (2015). The problem with workarounds is that they work: The persistence of resource shortages. *Journal of Operations Management*, *39–40*(1), 79–91. https://doi.org/10.1016/j.jom.2015.07.008

Moss, J., & Berner, E. S. (2015). Evaluating clinical decision support tools for medication administration safety in a simulated environment. *International Journal of Medical Informatics*, *84*(5), 308–318. https://doi.org/10.1016/j.ijmedinf.2015.01.018

Mueller, B., & Urbach, N. (2013). They Why, What, and How of Theories in IS

Research. *Thirty Fourth International Conference on Information Systems*, *May*, 1–25.

Mulder, N. (2005). *Mysticism in Java: ideology in Indonesia*. Kanisius.

Murray, D. S. (1971). That's Interesting: Towards a Phenomenology of Sociology and a Sociology of Phenomenology. *Philosophy of the Social Sciences*, *4*, 309–344.

Myers, M. (2009). *Qualitative Research in Business and Management*. Sage Publications.

Myers, Starliper, M. W., Summers, S. L., & Wood, D. A. (2017). The impact of shadow IT systems on perceived information credibility and managerial decision making. *Accounting Horizons*, *31*(3), 105–123. https://doi.org/10.2308/acch-51737

Nagle, T., Redman, T., & Sammon, D. (2020). Assessing data quality: A managerial call to action. *Business Horizons*, *63*(3), 325–337. https://doi.org/10.1016/j.bushor.2020.01.006

Nagle, T., & Sammon, D. (2017). The Data Value Map: A Framework for developing shared understanding on data initiatives. *ECIS 2017 Proceedings*, *2017*, 1439–1452.

NCES. (1997). *Protecting the Privacy of NCE*. National Center for Education Statistics. https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=97527

Nevo, S., Nevo, D., & Pinsonneault, A. (2016). A temporally situated self-agency theory of information technology reinvention. *MIS Quarterly*, *40*(1), 157. https://www.misq.org/skin/frontend/default/misq/pdf/appendices/2016/V40I1Appendices/07_12276_TR_NevoAppendix.pdf

Niazkhani, Z., Pirnejad, H., Sijs, H. Van Der, & Aarts, J. (2011). Evaluating the medication process in the context of CPOE use : The significance of working around the system. *International Journal of Medical Informatics*, *80*(7), 490–506. https://doi.org/10.1016/j.ijmedinf.2011.03.009

Nielsen, O. B. (2017). A Comprehensive Review of Data Governance Literature. *Information Systems Research Seminar in Scandinavia*. http://aisel.aisnet.org/iris2017http://aisel.aisnet.org/iris2017/3

Paré, G., Trudel, M. C., Jaana, M., & Kitsiou, S. (2015). Synthesizing information systems knowledge: A typology of literature reviews. *Information and Management*, *52*(2), 183–199. https://doi.org/10.1016/j.im.2014.08.008

Patton, M. Q. (2015). *Qualitative Research & Evaluation Methods : Integrating Theory and Practice*. SAGE.

Pentland, B. T. (1999). Organizations as Networks of Action. In *Variations in Organization Science: Essays in Honor of Donald T. Campbell,*.

Pentland, B. T., & Feldman, M. (2005). Organizational routines as a unit of analysis. *Industrial and Corporate Change*, *14*(5), 793–815. https://doi.org/10.1093/icc/dth070

Pentland, B. T., & Feldman, M. (2007). Narrative Networks : Patterns of Technology and Organization. *Organization Science*, *18*(5), 781–795. https://doi.org/10.1287/orsc.1070.0283

Pentland, B. T., & Feldman, M. (2008). Designing routines : On the folly of designing artifacts , while hoping for patterns of action. *Information and Organization*, *18*(4), 235–250. https://doi.org/10.1016/j.infoandorg.2008.08.001

Pentland, B. T., Feldman, M., Becker, M. C., & Liu, P. (2012). Dynamics of Organizational Routines : A Generative Model. *Journal of Management Studies*. https://doi.org/10.1111/j.1467-6486.2012.01064.x

Pentland, B. T., & Hærem, T. (2015). Organizational Routines as Patterns of Action : Implications for Organizational Behavior. *The Annual Review of Organizational Psychology and Organizational Behavior*, *2*, 465–87. https://doi.org/10.1146/annurev-orgpsych-032414-111412

Pentland, B. T., Hærem, T., & Hillison, D. (2010). Comparing Organizational Routines as Recurrent Patterns of Action. *Organizational Studies*, *31*(7), 917–940. https://doi.org/10.1177/0170840610373200

Pentland, B. T., Mahringer, C. A., Dittrich, K., Feldman, M. S., & Wolf, J. R. (2020). Process Multiplicity and Process Dynamics: Weaving the Space of Possible Paths. *Organization Theory*, *1*(3), 263178772096313. https://doi.org/10.1177/2631787720963138

Pentland, B. T., Recker, J., & Wyner, G. (2017). Rediscovering Handoffs. *Academy of Management Discovery*, *3*(3), 284–301. https://doi.org/10.5465/amd.20160018

Pipino, L. L., Lee, Y. W., & Wang, R. Y. (2002). Data Quality Assessment. *Communications of the ACM*, *45*(4), 211–218. https://doi.org/10.1145/505248.506010

Pirttimäki, V., & Liew, A. (2019). Does shortened reporting cycle improve quality of external financial reporting? *Journal of Applied Accounting Research*, *20*(3), 321–341. https://doi.org/10.1108/JAAR-02-2018-0035

Plotkin, D. (2014). *Data Stewardship: An Actionable Guide to Effective Data Management and Data Governance*. Morgan Kaufmann. https://doi.org/10.1080/15536548.2014.974401

Porter, M. (1985). *The Competitive Advantage: Creating and Sustaining Superior Performance*. Free Press.

Powell, S. G., Baker, K. R., & Lawson, B. (2008). A critical review of the literature on spreadsheet errors. *Decision Support Systems*, *46*(1), 128–138.

https://doi.org/10.1016/j.dss.2008.06.001

Redman. (2016a). Data Quality Should Be Everyone's Job. *Harvard Business Review*. https://hbr.org/2016/05/data-quality-should-be-everyones-job

Redman, T. (1998). The impact of Poor Data Quality on the Typical Enterprise. *Communications of the ACM*, *41*(2), 79–82.

Redman, T. (2013). Data ' s Credibility Problem. *Harvard Business Review*, *December*.

Redman, T. (2016b). *Getting in Front on Data: Who Does What*. Technics Publications.

Reiz, A., & Gewald, H. (2016). Physicians' resistance towards information systems in healthcare: The case of workarounds. *Pacific Asia Conference on Information Systems, PACIS 2016 - Proceedings*. https://aisel.aisnet.org/pacis2016/12

Ridder, H. G. (2017). The theory contribution of case study research designs. *Business Research*, *10*(2), 281–305. https://doi.org/10.1007/s40685-017-0045-z

Robey, D., & Markus, M. L. (1998). Beyond Rigor and Relevance: Producing Consumable Research about Information Systems. *Information Resources Management Journal (IRMJ)*, *11*(1), 7–16. https://doi.org/10.4018/irmj.1998010101

Robison, R. (1981). Culture, Politics, and Economy in the Political History of the New Order. In *Indonesia* (Vol. 31, pp. 1–29). Cornell University Press.

Röder, N., Wiesche, M., & Schermann, M. (2014). A Situational Perspective on Workarounds in IT-Enabled Business Processes: A Multiple Case Study. *European Conference on Information Systems*, *January*. http://aisel.aisnet.org/ecis2014/proceedings/track06/6

Röder, N., Wiesche, M., Schermann, M., & Krcmar, H. (2014). Why Managers Tolerate Workarounds – The Role of Information Systems. *Twentieth Americas Conference on Information Systems*, *January*.

Röder, N., Wiesche, M., Schermann, M., & Krcmar, H. (2015). Workaround Aware Business Process Modeling. *Proceedings Der 12. Internationalen Tagung Wirtschaftsinformatik (WI 2015)*, *12*, 482–496. http://www.wi2015.uni-osnabrueck.de/Files/WI2015-D-14-00259.pdf

Rodger, R. (Richard J. (2011). *Beginning mobile application development in the cloud*. John Wiley.

Romero, A., Gonzales, A., & Raymundo, C. (2019). Data Governance Reference Model under the Lean Methodology for the Implementation of Successful Initiatives in the Peruvian Microfinance Sector. *ICSIE '19 Proceedings of the 2019 8th International Conference on Software and Information Engineering*,

227–231.

Rowe, F. (2014). What literature review is not: Diversity, boundaries and recommendations. *European Journal of Information Systems*, *23*(3), 241–255. https://doi.org/10.1057/ejis.2014.7

Rubbio, I., Bruccoleri, M., Pietrosi, A., & Ragonese, B. (2018). Digital Health Technology Enhances Resilient Behaviour: Evidence from the Ward. *International Journal of Operations and Production Management*. https://doi.org/http://dx.doi.org/10.1108/MRR-09-2015-0216

Safadi, H., & Faraj, S. (2010). The Role of Workarounds During an Opensource Electronic Medical Record Implementation. *International Conference on Information Systems*.

Saleem, J. J., Russ, A. L., Justice, C. F., & Hagg, H. (2009). Exploring the persistence of paper with the electronic health record. *International Journal of Medical Informatics*, *8*(9), 618–628. https://doi.org/10.1016/j.ijmedinf.2009.04.001

Saleem, J. J., Russ, A. L., Neddo, A., & Blades, P. T. (2011). Paper persistence , workarounds , and communication breakdowns in computerized consultation management. *International Journal of Medical Informatics*, *80*(7), 466–479. https://doi.org/10.1016/j.ijmedinf.2011.03.016

Sandberg, J., & Alvesson, M. (2011). Ways of constructing research questions: Gap-spotting or problematization? *Organization*, *18*(1), 23–44. https://doi.org/10.1177/1350508410372151

Sanjari, M., Bahramnezhad, F., Fomani, F. K., Sho-Ghi, M., & Cheraghi, M. A. (2014). Ethical challenges of researchers in qualitative studies: the necessity to develop a specific guideline. *Journal of Medical Ethics and History of Medicine*, *7*(14), 1–6. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4263394/pdf/jmehm-7-14.pdf

Schwalbe, K. (2021). *An Introduction to Project Management, Seventh Edition: Predictive, Agile, and Hybrid Approaches*. Schwalbe Publishing.

Schwester, R. W. (2015). The Unit of Analysis and Variables. In *Teaching research methods in public administration* (p. 313).

Sebastian-Coleman, L. (2013). *Measuring Data Quality for Ongoing Improvement: A Data Quality Assessment Framework* (L. Sebastian-Coleman (ed.)). Morgan Kaufmann. https://doi.org/https://doi.org/10.1016/B978-0-12-397033-6.00020-1

Ser, G., Robertson, A., & Sheikh, A. (2014). A qualitative exploration of workarounds related to the implementation of national electronic health records in early adopter mental health hospitals. *PLoS ONE*, *9*(1), 1–9. https://doi.org/10.1371/journal.pone.0077669

Silic, M., & Back, A. (2014). Shadow IT - A view from behind the curtain. *Computers and Security*, *45*, 274–283. https://doi.org/10.1016/j.cose.2014.06.007

Silic, M., Barlow, J. B., & Back, A. (2017). A new perspective on neutralization and deterrence: Predicting shadow IT usage. *Information and Management*, *54*(8), 1023–1037. https://doi.org/10.1016/j.im.2017.02.007

Sillic, M. (2019). Critical impact of organizational and individual inertia in explaining non-compliant security behavior in the Shadow IT context. *Computers and Security*, *80*, 108–119. https://doi.org/10.1016/j.cose.2018.09.012

Silvius, A. G., & Dols, T. (2012). Factors influencing Non-Compliance behavior towards Information Security Policies. *International Conference on Information Resources Management (CONF-IRM)*.

Singh, H. (2015). Emergence and consequences of drift in organizational information systems. *Pacific Asia Conference on Information Systems (PACIS) 2015 Proceedings*. http://ezproxy.library.uvic.ca/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=2011-99030-492&site=ehost-live&scope=site

Sparrowe, R. T., & Mayer, K. J. (2011). Publishing in AMJ-part 4: Grounding hypotheses. *Academy of Management Journal*, *54*(6), 1098–1102. https://doi.org/10.5465/amj.2011.4001

Spierings, A., Kerr, D., & Houghton, L. (2017). Issues that support the creation of ICT workarounds: towards a theoretical understanding of feral information systems. *Information Systems Journal*, *27*(6), 775–794. https://doi.org/10.1111/isj.12123

Steinhueser, M., Waizenegger, L., Vodanovich, S., & Ritcher, A. (2017). Knowledge management without management- Shadow IT in Knowledge-Intensive Manufacturing Practices. *Twenty-Fifth European Conference on Information Systems (ECIS)*, *2017*, 1647–1662. https://pure.itu.dk/portal/files/82377908/2017_Steinh_ser_et_al_ECIS_KM_without_Mgt.pdf

Stevenson, J. E., Israelsson, J., Nilsson, G., Petersson, G., & Bath, P. A. (2018). Vital sign documentation in electronic records: The development of workarounds. *Health Informatics Journal*, *24*(2), 206–215. https://doi.org/10.1177/1460458216663024

Strong, D. M., Lee, Y. W., & Wang, R. Y. (1997). Data quality in context DQ problems. *Communications of the ACM*, *40*(5), 103–110. http://delivery.acm.org/10.1145/260000/253804/p103-strong.pdf?ip=141.59.82.181&id=253804&acc=ACTIVE SERVICE&key=2BA2C432AB83DA15.6118EF98202DC727.4D4702B0C3E38B35.4D4702B0C3E38B35&__acm__=1519660767_f4fa7913c4dfb8d4987d460a4b761e1b%0Ahttp://portal.acm.org

Suddaby, R. (2010). Editor's Comments: Construct Clarity in Theories of Management and Organization. *Academy of Management Review*, *35*(3), 367–357. https://doi.org/10.1016/S0009-2797(86)80089-8

Sullivan, J. (1986). Kampung and State : The Role of Government in the Development of Urban Community in Yogyakarta. *Indonesia*, *41*, 63–88. https://www.jstor.org/stable/3351036

Summers, G. (2004). *Developing databases with Access*. Cengage Learning.

Sutton, R. I., & Staw, B. M. (1995). What Theory is Not. *Administrative Science Quarterly*, *40*(3), 371–384. https://doi.org/10.1177/0090591701029005004

Teo, T. S. H., & Tan, M. (1997). Quantitative and qualitative errors in spreadsheet development. *Proceedings of the Hawaii International Conference on System Sciences*, *3*, 149–155. https://doi.org/10.1109/HICSS.1997.661583

The Data Warehousing Institute. (2010). *TDWI Data Governance Fundamentals*. 174.

Thriemer, K., Ley, B., Ame, S. M., Puri, M. K., Hashim, R., Chang, N. Y., Salim, L. A., Ochiai, R. L., Wierzba, T. F., Clemens, J. D., Von Seidlein, L., Deen, J. L., Ali, S. M., & Ali, M. (2012). Replacing paper data collection forms with electronic data entry in the field: Findings from a study of community-acquired bloodstream infections in Pemba, Zanzibar. *BMC Research Notes*, *5*(1), 113. https://doi.org/10.1186/1756-0500-5-113

Toffel, M. W. (2016). Enhancing the Practical Relevance of Research. *Production and Operations Management*, *25*(9), 1493–1505. https://doi.org/10.1111/poms.12558

Uppatumwichian, W., Johansson, B., & Carlsson, S. (2011). Accounting solutions use for budgeting in ERP, hybrid ERP, and BoB: An explorative study. *PACIS 2011 - 15th Pacific Asia Conference on Information Systems: Quality Research in Pacific*, 1–16. https://doi.org/ISBN: 978-1-86435-644-1

Van de Weerd, I., Vollers, P., Beerepoot, I., & Fantinato, M. (2019). Workarounds in retail work systems: prevent, redesign, adopt or ignore? *Twenty-Seventh European Conference on Information Systems*, 1–15.

van den Hooff, B., & Hafkamp, L. (2017). Dealing with Dissonance: Misfits between an EHR System and Medical Work Practices. *Thirty-Eighth International Conference on Information Systems*, 0–17.

Vassilakopoulou, P., Tsagkas, V., & Marmaras, N. (2012). Workaround identification as an instrument for work analysis and design: A case study on ePrescription. *Work*, *41*(SUPPL.1), 1805–1810. https://doi.org/10.3233/WOR-2012-0389-1805

Vilminko-Heikkinen, R., & Pekkola, S. (2019). Changes in roles, responsibilities and ownership in organizing master data management. *International Journal of*

Information Management, *47*(April 2018), 76–87. https://doi.org/10.1016/j.ijinfomgt.2018.12.017

Vogelsmeier, A. A., Halbesleben, J. R. B., & Scott-Cawiezell, J. R. (2008). Technology Implementation and Workarounds in the Nursing Home. *Journal of America Medical Informatics*, *15*, 114–119. https://doi.org/10.1197/jamia.M2378

Vojvodic, M., & Hitz, C. (2019). Governance Team Leadership and Business User Participation – Organizational Practices for Innovative Customer Engagement in Data Compliance Project. *Central European Business Review*, *8*(2), 15. https://doi.org/10.18267/j.cebr.214

Walsham, G. (1995). Interpretive case studies in IS research: Nature and method. *European Journal of Information Systems*, *4*(2), 74–81. https://doi.org/10.1057/ejis.1995.9

Walterbusch, M., Fietz, A., Tauteberge, F., & Teuteberg, F. (2017). Missing cloud security awareness: investigating risk exposure in shadow IT. *Journal of Enterprise Information Management*, *30*(4), 644–665. https://doi.org/10.1108/09574090910954864

Walters, R. (2013). Bringing IT out of the shadows. *Network Security*, *2013*(4), 5–11. https://doi.org/10.1016/S1353-4858(13)70049-7

Wang, R. Y., Storey, V. C., & Firth, C. P. (1995). A Framework for Analysis of Data Quality Research. *IEEE Transactions on Knowledge and Data Engineering*, *7*(4), 623–640. https://doi.org/10.1109/69.404034

Wang, R. Y., & Strong, D. M. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. *Journal of Management Information Systems*, *12*(4), 5–33. https://doi.org/10.2307/40398176

Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, *26*(2), xiii–xxiii. https://doi.org/10.1.1.104.6570

Weick, K. E. (1989). Theory Construction as Disciplined Imagination. *Academy of Management Review*, *14*(4), 516–531. https://doi.org/10.5465/amr.1989.4308376

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the Process of Sensemaking. *Organization Science*, *16*(4), 409–421. https://doi.org/10.1287/orsc.1050.0133

Weygandt, J. J., Kimmel, P. D., & Kieso, D. E. (2014). *Managerial Accounting: Tools for Business Decision Making* (7th ed.). Wiley.

Wibisono, A., Sammon, D., & Heavin, C. (2020). Modelling data activities in workarounds: a narrative network approach. *Journal of Decision Systems*,

29(Sup1), 1–12. https://doi.org/10.1080/12460125.2020.1778874

Wibisono, A., Sammon, D., & Heavin, C. (2022a). Data availability issues : decisions as patterns of action. *Journal of Decision Systems*, 1–14. https://doi.org/10.1080/12460125.2022.2070945

Wibisono, A., Sammon, D., & Heavin, C. (2022b). Opening the workaround black box: an organisational routines perspective. *Journal of Decision Systems*. https://doi.org/https://doi.org/10.1080/12460125.2022.2073647

Wibisono, A., Sammon, D., & Heavin, C. (2022c). Plausible Pictures for Data Governance: A Narrative Network Approach. *30th European Conference on Information Systems*. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1109&context=ecis2022_rp

Wibisono, A., Sammon, D., Heavin, C., & Alhassan, I. (2021). *Workaround-centric Data Activities*.

Wibisono, A., Sammon, D., Heavin, C., & Alhassan, I. (2022). Theorising Workaround-centric Data Issues: A Literature Analysis. *SSRN Journal*. https://doi.org/http://dx.doi.org/10.2139/ssrn.4242499

Wiggins, A., Newman, G., Stevenson, R. D., & Crowston, K. (2011). Mechanisms for data quality and validation in citizen science. *Proceedings - 7th IEEE International Conference on e-Science Workshops, EScienceW 2011*, 14–19. https://doi.org/10.1109/eScienceW.2011.27

Wolf, V., Bartelheimer, C., & Beverungen, D. (2020). *Workarounds as Generative Mechanisms for Restructuring and Redesigning Organizations Insights from a Multiple Case Study* (No. 2020–09).

Wolf, V., & Beverungen, D. (2019). Conceptualizing the impact of workarounds - an organizational routines' perspective. *Twenty-Seventh European Conference on Information Systems (ECIS2019)*, 0–11.

Wolfswinkel, J. F., Furtmueller, E., & Wilderom, C. P. M. (2011). Using grounded theory as a method for rigorously reviewing literature. *European Journal of Information Systems*, *22*(1), 45–55. https://doi.org/10.1057/ejis.2011.51

Xian, Y., Fonarow, G. C., Reeves, M. J., Webb, L. E., Blevins, J., Demyanenko, V. S., Zhao, X., Olson, D. M., Hernandez, A. F., Peterson, E. D., Schwamm, L. H., & Smith, E. E. (2012). Data quality in the American Heart Association Get with the Guidelines-Stroke (GWTG-Stroke): Results from a National Data Validation Audit. *American Heart Journal*, *163*(3), 392-398.e1. https://doi.org/10.1016/j.ahj.2011.12.012

Yang, Z., Ng, B. Y., Kankanhalli, A., & Luen Yip, J. W. (2012). Workarounds in the use of IS in healthcare: A case study of an electronic medication administration system. *International Journal of Human Computer Studies*, *70*(1), 43–65.

https://doi.org/10.1016/j.ijhcs.2011.08.002

Yeow, A., & Faraj, S. (2011). Using Narrative Networks to Study Enterprise Systems and Organizational Change. *International Journal of Accounting Information Systems*, *12*(2), 116–125. https://doi.org/10.1016/j.accinf.2010.12.005

Yin, R. K. (2009). Case Study Research Fourth Edition. In *SAGE*. https://doi.org/10.1016/j.jada.2010.09.005

Zamani, E. D., Giaglis, G. M., & Pouloudi, A. (2013). A Sensemaking Approach to Tablet Users' Accomodating Practices. *Thirty Fourth International Conference on Information Systems*.

Zamani, E. D., & Pouloudi, N. (2020). Generative mechanisms of workarounds, discontinuance and reframing: a study of negative disconfirmation with consumerised IT. *Information Systems Journal*, *October*. https://doi.org/10.1111/isj.12315

Zhang, Q., Sun, X., & Zhang, M. (2022). Data Matters: A Strategic Action Framework for Data Governance. *Information and Management*, *59*(4), 103642. https://doi.org/10.1016/j.im.2022.103642

Zhao, J. Y., Kessler, E. G., & Guo, W. A. (2019). Interprofessional Communication Goes Up When the Electronic Health Record Goes Down. *Journal of Surgical Education*, *76*(2), 512–518. https://doi.org/10.1016/j.jsurg.2018.08.024

Zimmermann, S., & Rentrop, C. (2014). On the emergence of shadow IT - A transaction cost-based approach. *Twenty Second European Conference on Information Systems (ECIS)*, 1–17. https://doi.org/10.1007/s00227-002-0872-z

Zimmermann, S., Rentrop, C., & Felden, C. (2016). Governing Identified Shadow IT by Allocating IT Task Responsibilities. *Twenty-Second Americas Conference on Information Systems (AMCIS)*, *Picot 1990*, 1–10.

Zimmermann, S., Rentrop, C., & Felden, C. (2017). A Multiple Case Study on the Nature and Management of Shadow Information Technology. *Journal of Information Systems*, *31*(1), 79–101. https://doi.org/10.2308/isys-51579