UNIVERSITY OF TECHNOLOGY SYDNEY
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Collaborative Robot Technology Adoption in Australian Manufacturing SMEs

by

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Thesis Submitted
in Fulfillment of the
Requirements for the Degree

Doctor of Philosophy

under the supervision of
Farookh Khadeer Hussain

Sydney, Australia

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Mashael Haddas, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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ABSTRACT

Collaborative robots (cobots) represent an emerging category of technological innovation that is transforming the industrial landscape by revolutionising the interaction between machines and humans. Cobots are lightweight, cost-effective and flexible industrial solutions that have become increasingly suited to the growing shift toward mass customisation in modern manufacturing environments. Despite their potential and promise, especially for small and medium-sized enterprises (SMEs), adoption among SMEs remains relatively limited, with several challenges related to their adoption still unexplored.

Driven by 1) the strategic importance of advanced technologies for developing manufacturing SMEs in Australia, and 2) the limited research on cobot adoption in this context, the present study aims to develop the Holistic Collaborative Robot Adoption Model (HCRAM) for Australian manufacturing SMEs.

Guided by the design science approach, this thesis makes the following contributions: 1) it develops a conceptual framework grounded in both empirical and theoretical research on cobot adoption in the manufacturing sector; 2) it presents findings from the analysis and refinement of the conceptual framework based on perspectives from senior and mid-level managerial and technical specialists; and 3) it demonstrates the evaluation outcomes of the framework in manufacturing SMEs, drawing on data gathered from a large sample using the questionnaire instrument.

The HCRAM, developed in this thesis, is, to the best of the researcher's knowledge, the first to address this issue in the context of Australian manufacturing SMEs. It encompasses five key contexts relevant to cobot adoption: environment, human, technology, organisation, and barriers. The findings show that 11 of the 15 factors demonstrated a statistically significant association with cobot adoption, thereby supporting the validity of the findings. As a result, HCRAM can be used as a practical tool for industrial decision-makers to formulate adoption strategies for cobots in Australian manufacturing SMEs. It is supported by an online questionnaire tool designed to identify both enablers and barriers to adoption across a wide range of

Australian manufacturing SMEs. It further establishes a basis for future work on cobot adoption within manufacturing SMEs and related contexts.

Although this thesis employs a rigorous approach, there are several limitations relating to data collection, sampling methods, and geographic context. Therefore, future research could adopt different methodologies to further validate HCRAM and explore its applicability across various industries and national contexts.

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To my dearest mother, Fatimah, I owe endless gratitude for her love, prayers, and patience. Her support has been a constant source of strength guiding me along this path.

To my son, Rakan, you are my light and motivation. Your presence has given me strength during the most difficult moments and inspired me to never give up.

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Mashael Haddas

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List of Publications

The following are the research contributions published or submitted throughout my PhD candidature:

Conference Papers

- M. Haddas and F.K. Hussain, "Technology Factors Affecting Australian Manufacturing SMEs Adoption of Collaborative Robot Technology: A Qualitative Interview Study,". In *Proceedings of the 43rd International Business Information Management Association Conference (IBIMA)*, Madrid, Spain, June 2024.
- M. Haddas and F.K. Hussain, "Human Factors Influencing Australian Manufacturing SMEs' Adoption of Collaborative Robots: A Qualitative Study. In *Advanced Information Networking and Applications: Proceedings of the 39th International Conference on Advanced Information Networking and Applications (AINA-2025)*, vol. 7, Cham, Switzerland: Springer, 2025, pp. 154-164.

Journal Papers

- Mashael Haddas, and Farookh Khadeer Hussina. "Cobots in Manufacturing SMEs: A Systematic Literature Review of Adopter Factors and Barriers", (under preparation).

Abbreviations

ABS	Australian Bureau of Statistics
ACT	Australian Capital Territory
AMOS	Analysis of Moment Structures
AMTIL	Australian Manufacturing Technology Institute Limited
ASBEFO	Australian Small Business and Family Enterprise Ombudsman
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Composite Reliability
DOI	Diffusion of Innovations
EFA	Exploratory Factor Analysis
H	Hypothesis
HRI	Human-Robot Interaction
HRC	Human-Robot Collaboration
IFI	Incremental Fit Index
IS	Information System
IT	Information Technology
KMO	Kaiser-Meyer-Olkin
NFI	Normed Fit Index
NSW	New South Wales
NT	Northern Territory
QLD	Queensland
RMSEA	Root Mean Square Error of Approximation
SA	South Australia
SEM	Structural Equation Modelling

SPSS	Statistical Package for the Social Sciences
SMEs	Small and Medium-sized Enterprises
SRMR	Standardised Root Mean Residual
STS	Sociotechnical System
TAS	Tasmania
TLI	Tucker-Lewis Index
TOE	Technology, Organisation and Environment
VIC	Victoria
VIF	Variance Inflation Factor
WA	Western Australia

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Overview

Chapter 1 presents the introductory context of the study. Section 1.2 presents the background of this thesis. The scope presented in section 1.3. Section 1.4 highlights the significance and expected contributions of the work. Section 1.5 provides an overview of the thesis layout.

1.2 Research Background

Robotics has long contributed to Australia's industrial development, particularly in mining, logistics, and large-scale manufacturing. Early adoption focused on traditional industrial robots, which were designed for repetitive, hazardous, and high-volume tasks. While effective in these settings, such systems were expensive, technically complex, and largely inaccessible to Australian small and medium-sized enterprises (SMEs), defined as businesses with between 1 and 199 employees [8]. As a result, much of the manufacturing sector remained labour-intensive, limiting productivity growth and reducing competitiveness in global markets [8].
Today, manufacturing remains a cornerstone of economic growth, supporting job creation and industrial expansion. In Australia, this sector is dominated by SMEs, which overall represent 66% of the workforce and contribute 50% of the total value added [9]. Despite recent growth, persistent challenges, including high labour costs, skills shortages, and limited access to automation, continue to restrict competitiveness [8]. The COVID-19 pandemic increased existing challenges by exposing structural vulnerabilities in supply chains and labour availability [10]. Following the disruptions of COVID-19, resilience and digital transformation have emerged as the main priorities for policymakers and industry leaders seeking recovery and

sustained competitiveness [10] Furthermore, in light of these constraints, the Australian Government's strategic vision for 2030 prioritises digital transformation and industrial innovation as critical to national resilience [11]. In this context, collaborative automation has emerged as a key enabler for SMEs, providing an accessible and adaptable alternative to conventional robotics [11, 12].

Among the most significant technological advances reshaping advanced manufacturing are cobots. Unlike conventional robots, cobots are developed to work with operators without protective fencing, enabling real human–robot collaboration [13],[14],[15], [16]. The key difference of traditional systems is their ability to share overlapping workspaces with operators. Levels of collaboration vary, from basic coexistence through to true collaboration where humans and robots simultaneously collaborate on a common task [14]. To ensure safe operation, international standards such as ISO/TS 15066:2016 provide detailed requirements, with most modern cobots designed to comply with these safety specifications [16].

Cobots are increasingly deployed to help workers with repetitive or physically demanding tasks, assist with high-precision activities, and reduce workload in production environments [14]. The most common applications in manufacturing include assembly, packing, and palletising [17],[18]. These features make cobots a promising technology for SMEs seeking greater efficiency and flexibility. However, adoption decisions remain complex, determined by financial analysis and the difficulty of measuring certain qualitative benefits [19]. While government policy frameworks recognise cobots as part of Australia's list of critical technologies in the national interest [11], empirical evidence of their adoption by SMEs remains limited. Addressing this gap is vital, as SMEs form the backbone of Australia's manufacturing sector, and understanding the organisational, technological, environmental, and human factors influencing cobot adoption can offer benefit insights for policymakers.

1.3 Thesis scope

This study is limited to the Australian context, with a specific focus on manufacturing SMEs. It investigates the early stage of cobot adoption in this sector, drawing primarily on the perspectives of decision-makers, including top and mid-level managers as well as technical experts. The views of shop-floor workers are not included within the scope of this study and remain an important area for future research.

1.4 Significance of the Thesis

Although cobots are widely recognised as an emerging technology in advanced manufacturing, the research on their adoption remains fragmented and incomplete. Some existing work has examined technical concerns and user preferences at the production technology level [15]. Other studies have addressed organisational human factors [20], while some focus on individual level aspects such as operator attitudes [21]. With regard to adoption decision-making, evidence at the organisational level is limited. For example, studies conducted in China [22] and Portugal [23] investigated SMEs using quantitative survey methods, while research by [24] examined large firms in Portugal through qualitative interviews. While valuable, these studies differ in scope and methodology, and their findings are strongly determined by national and industrial contexts.

Despite growing global interest, little is known about the decision-making processes and barriers influencing cobot use within manufacturing SMEs. In particular, human factors, such as managerial perceptions, have not been consistently integrated into adoption models, as well as barriers. This presents significant gaps in understanding how SMEs, which often face resource and skills constraints, approach investment in collaborative automation.

Most importantly, to the best of the author's knowledge, no empirical research has examined cobot adoption in Australian manufacturing SMEs. This gap is critical, provided the primary role of SMEs in Australia's economy, where they account for two thirds of the manufacturing workforce and contribute substantially to industrial output. Without context-specific evidence, government strategies and industry initiatives promoting digital transformation risk being poorly aligned with the actual challenges faced by SMEs. The current work aims to overcome this gap by identifying organisational, technological, environmental, and human determinants and barriers to cobot adoption in Australian SMEs.

1.4.1 Theoretical Contributions

- The research extends existing adoption theories by exploring additional factors relevant to cobot adoption in Australian manufacturing SMEs. It offers a more comprehensive model by integrating relevant theoretical constructs.

- This research develops a refined framework for cobot adoption in manufacturing SMEs and examines it in a new context. Furthermore, it considers both new contextual elements and existing theoretical factors.

- This research examines the applicability of established theories in Australia.

1.4.2 Practical Contributions

- This research develops a practical model for cobot adoption that identifies the factors facilitating and impeding its use in Australian manufacturing SMEs.

- The study provides a structured roadmap for implementing a cobot to support decision makers in Australian manufacturing SMEs.

- The research provides a validated measurement tool (survey) designed to study adoption comprehensively across multiple factors or more specifically at the level of individual dimensions.

- The study represents the first empirical investigation to explore the combined effect of environmental, organisational, technological human factors, to the author's knowledge, along with potential barriers, on cobot adoption within Australian manufacturing SMEs. It provides a foundation for designing a practical tool to support manufacturing SMEs and potentially the broader sector in making informed decisions on the timing and manner of adoption.

1.5 Thesis Layout

There are nine chapters in this work, as depicted in Figure 1.1, as follows:

Chapter 1 offers the study background, outlines the scope, significance, and contribution of the research.

Chapter 2 offers a review of cobot adoption in manufacturing SMEs. It provides a taxonomy of the available literature, covering the reasons for adoption, barriers and facilitating factors, and the theoretical models applied to explain adoption. Based on this review, the chapter also identifies key research gaps.

Chapter 3 presents the objectives and research questions.

Chapter 4 offers the research solution developed to investigate the research questions and describes the methods that guided this work.

Chapter 5 introduces the Holistic Collaborative Robot Adoption Model (HCRAM), developed by the researcher to examine cobot adoption in manufacturing SMEs. It also presents the hypotheses developed to guide the study.

Chapter 6 provides Phase 1 of the study, which adopts a qualitative design.

Chapter 7 offers Phase 2 of the study, which adopts a quantitative design.

Chapter 8 highlights a discussion of both phases of the current work.

Chapter 9 outlines conclusion and recommendations for future studies.

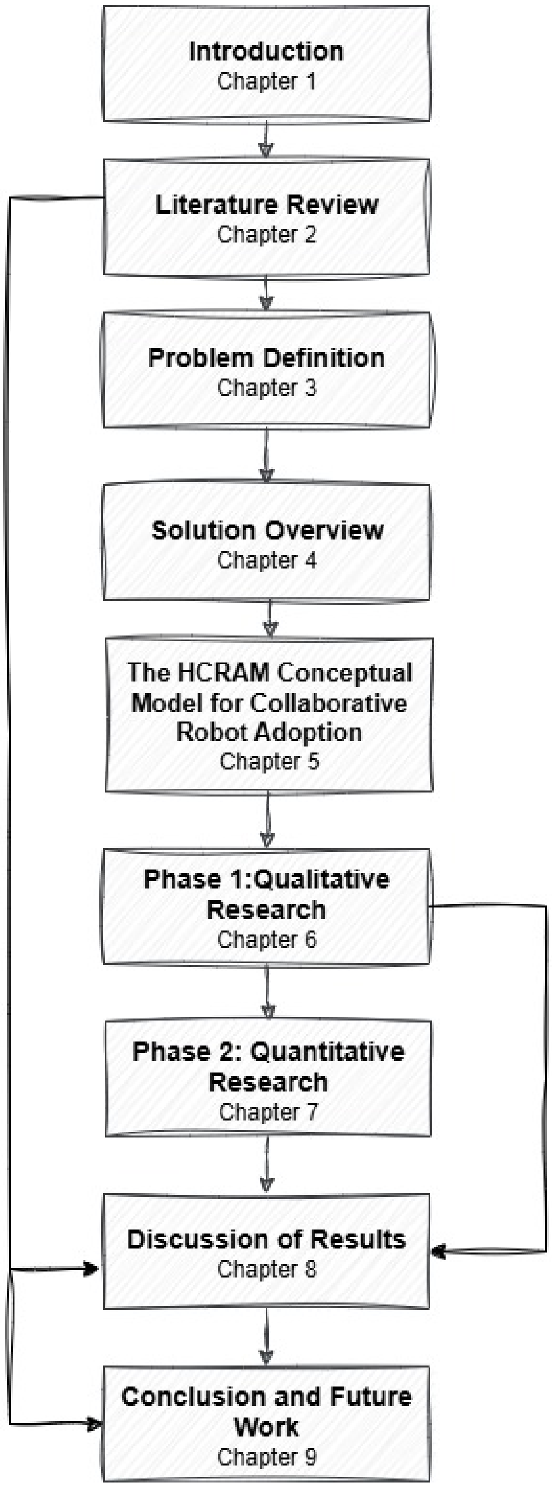

Figure 1.1 : Thesis Structure

Chapter 2

A Systematic Literature Review

2.1 Overview

This systematic literature review aims to provide an overview and analysis of the existing studies related to collaborative robot (cobot) adoption in manufacturing SMEs. This chapter focuses on three main areas: evidence of cobot adoption in manufacturing SMEs, motivations/reasons driving cobot adoption in this context, and related factors and barriers that influence the adoption process. A well-defined methodological protocol for identifying, screening, and selecting the shortlist papers is presented, and the themes for cobot and applications/uses in manufacturing SMEs are analysed. The results are utilised to highlight existing knowledge gaps, thus presenting this study within the broader context of cobot adoption research in manufacturing SMEs.

The structure of this chapter is as follows. Section 2.2 outlines the SLR protocol applied to the shortlisted studies, including the inclusion and exclusion criteria during the literature search, as well as an overview of the extracted papers by publication type and year. Section 2.3 presents the discussion and analysis of the shortlist papers structured around five components aligned with the SLR research questions: (1) a review of the evidence regarding cobot adoption in the manufacturing area, (2) an outline of the main reasons/motivations driving cobot adoption in manufacturing SMEs, (3) an identification of the barriers to cobot adoption reported in the shortlist papers, (4) a summary of the adoption factors identified in the same set of papers, (5) a summary of the existing theories/models related to cobot adoption in manufacturing SMEs. The key research gaps emerging from the literature analysis are presented in Section 2.5. The limitations associated with this SLR are outlined in Section 2.4. The chapter concludes in Section 2.6.

2.2 Systematic Literature Review Protocol

This research uses a systematic literature review (SLR) protocol to explore the state of cobot adoption in manufacturing SMEs. An SLR is a rigorous, structured approach that enables researchers to analyse, interpret and synthesise existing studies to identify gaps in a defined research domain [1]. This review adopts the established SLR guidelines developed by Okolio [1] and Keel et al. [2], which are specifically designed for research in the information technology domain. The key aim of this review is to evaluate existing studies on cobot adoption and/or use in manufacturing to identify the drivers and barriers influencing adoption, examine the theoretical frameworks/models of adoption, and highlight critical gaps that require further study. Figure 2.1 illustrates the systematic review process used in this study, with a brief description of the four steps.

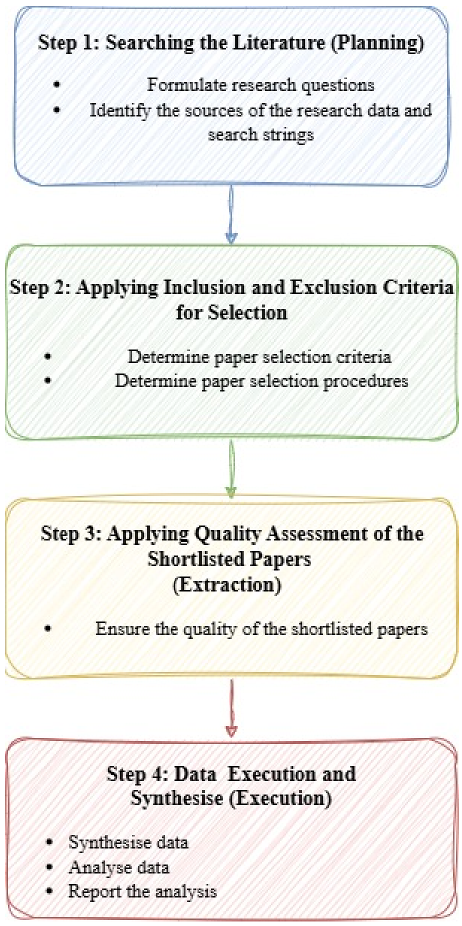

Figure 2.1 : Systematic Literature Review Process (adapted from [1],[2])

2.2.1 Searching the Literature

This review focuses on cobot adoption in the manufacturing sector, particularly SMEs. In light of the identified gaps in the current literature, this review aims to examine the factors that drive adoption, the barriers that impede it, and the theoretical frameworks/models commonly applied to cobot adoption in manufacturing SMEs. The research questions developed for the systematic review, along with the rationale supporting each, are presented in Table 2.1.

Table 2.1 : Systematic Literature Review Questions

Review Questions	**Purpose**
What evidence exists regarding cobot adoption in manufacturing environments?	To determine manufacturing areas where cobots have proven benefits and develop a taxonomy for research types.
What are the key reasons for cobot adoption in manufacturing environments?	To study and analyse the underlying motivations driving cobot adoption in manufacturing environments.
What are the barriers to cobot adoption in manufacturing environments?	To identify and categorise the barriers/challenges that prevent cobot adoption in manufacturing environments.
What are the various factors influencing the adoption of cobots in manufacturing environments?	To identify and categorise the various factors that facilitate cobot adoption in manufacturing environments.
What theoretical models/frameworks have been utilised to study cobot adoption in manufacturing environments?	To determine the theoretical models/frameworks that can benefit future empirical research on cobot adoption.

The literature search for this review was carried out using the following online databases. These databases were selected based on their high academic ranking and established reputation for indexing relevant and high-quality scholarly publications.

- ACM Digital Library (`https://dl.acm.org/`)
- IEEE Xplore (`https://ieeexplore.ieee.org`)

- PreQuest (https://www.prequest.com/)
- ScienceDirect https://sciencedirect.com
- Scopus (https://www.scopus.com/)
- SpringerLink (https://link.springer.com)

The search period was set between 2014 and 2024 (a decade), as before 2014, only limited academic attention was given to the topic of cobot adoption, particularly in relation to adoption factors and theoretical frameworks in manufacturing SMEs. Given the significant increase in literature on cobot adoption since 2014, this time frame is deemed suitable for this review. The search strategy for this review followed guidelines [1] and [2] for the search strings, which were designed according to the main themes from different key terms, research questions, and utilising Boolean operators. Table 2.2 presents the Boolean search strings applied across different databases to identify relevant papers on cobot adoption. Three main search focuses were used: cobot adoption in manufacturing, cobot adoption in manufacturing SMEs, and cobot applications in manufacturing. The search was expanded beyond SMEs because few papers focus only on SMEs.

Table 2.2 : Search Focus and Boolean Strings

Search Focus	Boolean String
Cobot adoption in manufacturing	(”Collaborative robot*” OR cobot* OR ”human-robot collaboration” OR ”HRC” OR ”Human-robot interaction” OR ”HRI” OR ”Industrial collaborative robot” OR ICR) AND (”adoption” OR ”acceptance” OR ”usage” OR ”use”) AND (manufacturing OR factory OR industr* OR production OR assembly)
Cobot adoption in manufacturing SMEs	(”Collaborative robot*” OR cobot* OR ”human-robot collaboration” OR ”HRC” OR ”Human-robot interaction” OR ”HRI” OR ”Industrial collaborative robot” OR ICR) AND (”adoption” OR ”acceptance” OR ”usage” OR ”use”) AND (manufacturing OR factory OR industr* OR production OR assembly) AND (SME* OR ”small and medium enterprise*” OR ”small-medium enterprise*” OR ”small medium enterprise*” OR ”small business*” OR ”medium-sized enterprise*”)
Cobot applications in manufacturing	(”Collaborative robot*” OR cobot* OR ”human-robot collaboration” OR ”HRC” OR ”Human-robot interaction” OR ”HRI” OR ”Industrial collaborative robot” OR ICR) AND (”application” OR ”usage” OR ”use”) AND (manufacturing OR factory OR industr* OR production OR assembly) OR (SME* OR ”small and medium enterprise*” OR ”small-medium enterprise*” OR ”small medium enterprise*” OR ”small business*” OR ”medium-sized enterprise*”)

2.2.2 Applying Inclusion and Inclusion Criteria

These criteria were established to identify relevant papers for the systematic review. These criteria are as follows:

Inclusion criteria:

- The paper was published between 2014 and 2024.
- The full text is published/available.
- The paper is a scientific publication such as a journal or conference paper.
- The paper relates to cobot adoption and/or use in manufacturing environments.

Exclusion criteria:

- Not written in the English language.
- Published in a book, a book chapter, thesis, newspaper, poster session, technical report, or magazine.
- Duplicate publications.
- Papers that primarily focus on the technical engineering of cobots, particularly on mechanical design, control algorithms, or hardware specifications.

To facilitate this process, the study utilised EndNote to store and manage the records of papers retrieved at each stage. Stage 1 involved an initial search across six academic databases using the search string detailed in Table 2.2, which yielded a total of 9021 papers: 584 from ACM, 978 from IEEE Xplore, 2328 from ProQuest, 1301 from Scopus, 2816 from Scopus, and 1014 from SpringerLink. Stage 2 consisted of an initial screening for duplicate papers, resulting in the elimination of 1207 duplicate papers. Stage 3 involved a title and abstract screening to assess eligibility using inclusion and exclusion criteria, which resulted in the elimination of another 7646 papers. In stage 4, quality assessment criteria (in-depth analysis) were applied on the remaining papers, which further reduced the number to 32 papers eligible for final inclusion in the SLR. More details about the quality assessment criteria are provided below. Figure 2.2 shows the paper filtration process.

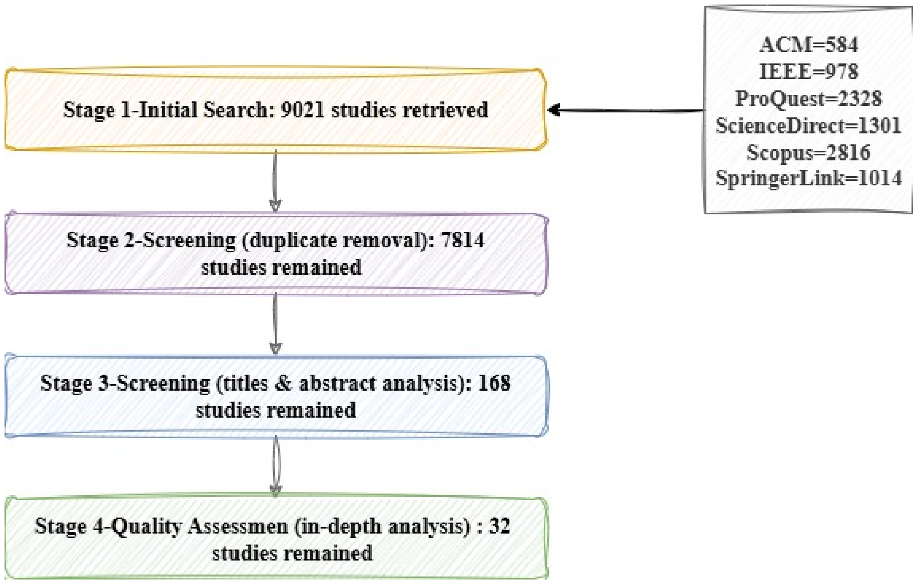

Figure 2.2 : Process of Paper Selection

2.2.3 Applying Quality Assessment to the Shortlisted Papers

In this step, a quality assessment was carried out for each paper to ensure its relevance for inclusion in the systematic review, and to reduce potential bias in the selection process. Table 2.3 provides the quality assessment questions and the associated grading criteria. A total of 168 full-text papers were evaluated using a predefined grading criterion, where responses were scored as follows: 1 point for "Yes", 0.5 for "Partially", and 0 for "No". A paper was deemed acceptable for inclusion in the final systematic review only if it achieved a minimum total score of 2.5.

Table 2.3 : Quality Assessment and Grading Criteria

Quality Assessment Question	Grading Criteria
1. Is the research purpose provided?	Yes=1 Partially=0.5 No=0
2. Is the study methodology clearly presented?	
3. Does the study demonstrate sufficient rigour in research execution and analysis?	
4. Does the study provide clear and suitable findings for practical use and/or academic studies?	

The 32 shortlisted papers that met the quality assessment criteria are listed in Table 2.4.

Table 2.4 : Shortlisted papers for the SLR

Paper	**Year**	**Title**
Charalambous et al.[20]	2015	Identifying the key organisational human factors for introducing human-robot collaboration in industry: an exemplary study.
Caltiz et al.[25]	2017	The future African workplace: The use of collaborative robots in manufacturing.
Kildal et al.[15]	2018	Potential users' key concerns and expectations for the adoption of cobots.
Aaltonen and Salmi[26]	2019	Experiences and expectations of collaborative robots in industry and academia: barriers and development needs.
Bröhl et al.[21]	2019	Human-Robot Collaborative Acceptance Model: Development and Comparison for Germany, Japan, China and the USA.
Accorsi et al.[27]	2019	An application of collaborative robots in a food production facility.
Hentout et al.[28]	2019	Human-robot interaction in industrial collaborative robotics: a literature review of the decade 2008-2017
Matheson et al.[29]	2019	Human-Robot Collaboration in Manufacturing Applications: A Review.
Simões et al.[24]	2020	Factors influencing the intention of managers to adopt collaborative robots (cobots) in manufacturing organisations.
Meissner et al.[30]	2020	Friend and Foe? Undertaining Assembly Workers' Acceptance of Human-Robot Collaboration.

Continued on next page

Table 2.4 (continued)

Paper	Year	Title
Pérez et al.[31]	2020	Symbiotic human-robot collaborative approach for increased productivity and enhanced safety in the aerospace manufacturing industry.
Kopp et al.[32]	2021	Success factors for introducing industrial human-robot interaction in practice: an empirically driven framework.
Cardoso et al.[33]	2021	Ergonomics and human factors as a requirement to implement safer collaborative robotic workstations: A literature review.
Segura et al.[34]	2021	Human-robot collaboration systems: Structural components for current manufacturing applications.
Ronzoni et al.[35]	2021	A support-design framework for Cooperative Robots system in labour-intensive manufacturing process.
Liu and Cao[22]	2022	Determinants of Collaborative Robots Innovation Adoption in Small and Medium-Sized Enterprises: An Empirical Study in China.
Zemlyak et al.[36]	2022	Assessing the Influence of Collaborative Technology Adoption-Mediating Role of Sociotechnical, Organisational and Economic Factors.
Baumgartner et al.[37]	2022	Analysing Factory Workers' Acceptance of Collaborative Robots: A Web-Based Tool for Company Representatives.
Schnell and Holm[38]	2022	Challenges for Manufacturing SMEs in the Introduction of Collaborative Robots.

Continued on next page

Table 2.4 (continued)

Paper	Year	Title
Liu et al.[22]	2022	Applications, Developments and Future Opportunities of Collaborative Robots (Cobots) in Manufacturing.
Berx et al.[39]	2022	Assessing System-Wide Safety Readiness for Successful Human-Robot Collaboration Adoption.
Prassida and Asfari[40]	2022	A conceptual model for the acceptance of collaborative robots in industry 5.0.
Faccio et al.[41]	2022	Human factors in cobot era: a review of modern production systems.
Berx et al.[42]	2022	Examining the Role of Safety in the Low Adoption Rate of Collaborative Robots.
Silva et al.[43]	2022	Criteria to consider in a decision model for collaborative robot (cobot) adoption: A literature review.
De Simone et al.[44]	2022	Human-Robot Collaboration: an analysis of worker's performance.
Giberti et al.[45]	2022	A Methodology for Flexible Implementation of Collaborative Robots Smart Manufacturing Systems.
Jennes and Di Minin[46]	2023	Cobots in SMEs: Implementation Process, Challenges, and Success Factors.
Barravecchia et al.[47]	2023	A general cost model to assess the implementation of collaborative robots in assembly processes.
Couto et al.[23]	2024	What Matters for Managers When Adopting Cobots in Manufacturing Organisations? The Results of a Survey Study in Portuguese SMEs.
Keshvarparast et al.[48]	2024	Collaboration robots in manufacturing and assembly systems: literature review and future research agenda.

Continued on next page

Table 2.4 (continued)

Paper	Year	Title
Polonara et al.[49]	2024	Introduction of Collaborative Robots in the Production of Automotive Parts: A Case Study.

2.2.4 Data Extraction and Synthesis Process

In step 4, the extracted data were synthesised to report on the shortlisted papers. Data were organised into themes aligned with the research question and presented through figures and tables to facilitate interpretation and analysis, as detailed in section 2.3.

2.3 Results and Discussion of the Shortlisted Papers

This section presents the main results of the systematic review. First, descriptive results are outlined, highlighting the distribution and publication characteristics of the reviewed papers. Figure 2.3 illustrates the distribution of research outputs by year. The number of published papers remained low and relatively stable between 2014 and 2018, followed by a gradual increase in subsequent years. Publication output peaked in 2022, with a total of 12 papers. This was followed by a decline to two papers in 2023, before increasing again to four papers in 2024. As 2024 data may still be incomplete, this figure may continue to increase. Regarding the distribution of research outputs by publication type., as shown in Figure 2.4, journal articles dominate the data set, with a substantial representation of conference publications as well. Next, the analysis of the shortlisted papers in relation to the research questions is presented.

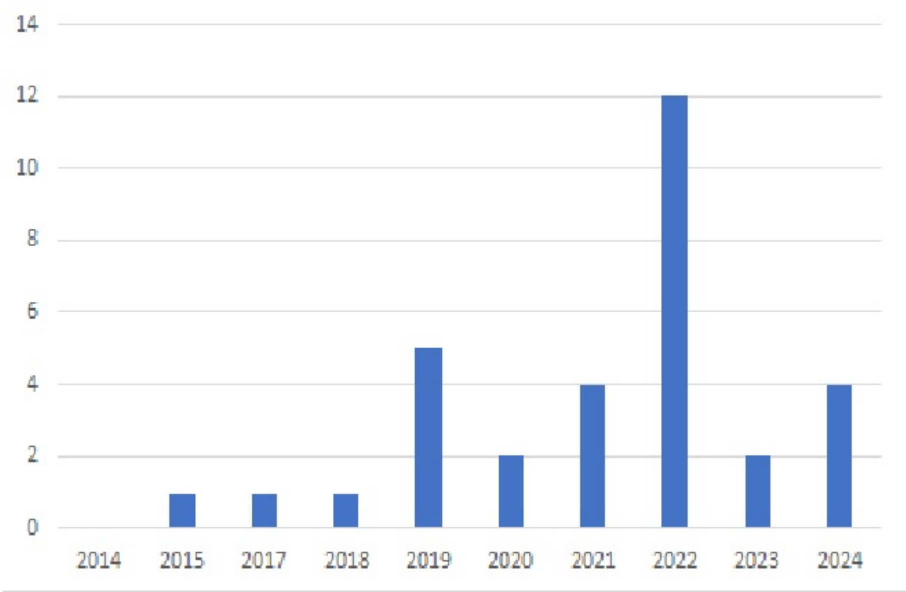

Figure 2.3 : Distribution of Research Outputs by Year

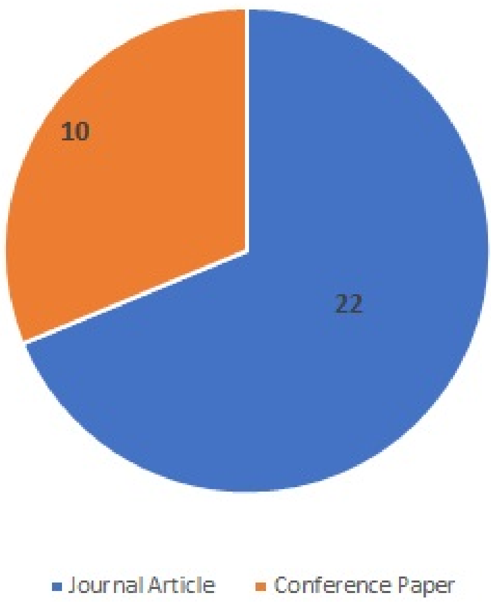

Figure 2.4 : Distribution of Research Outputs by Type

2.3.1 Evidence of Collaborative Robot Adoption in Manufacturing

To understand how research on cobot adoption in manufacturing has evolved, and to provide a clear overview of the evidence types available, a detailed mapping of research types was conducted. This process allows the improvement of a taxonomy for the shortlisted papers. A taxonomy refers to a systematic and structured approach to organising knowledge and information [50]. Several established approaches for developing a taxonomy of selected papers have been outlined by D. Porta and M. Keating [51],and Creswell [52]. While these approaches differ in how they classify papers, they share common methods for grouping knowledge based on research purpose or research methodology. This review adopted this approach. Figure 2.5 presents the research taxonomy developed in this study. As illustrated, three main research categories were identified: first, literature reviews examining cobot use in the manufacturing sector; second, research development stages, which include the conceptual stage, the tested (but not yet applied) stage, and the deployment (applied) stage for cobot applications and solutions; and third, empirical research on the factors that drive or impede cobot adoption in the manufacturing context. Within each category, some subcategories were identified based on research focus, research questions, and objectives. The same paper may be categorised under multiple subcategories with the research taxonomy due to its relevance and contribution to each area. Figure 2.5 provides a detailed analysis of each category. The same paper may be categorised under multiple subcategories within the research taxonomy due to its relevance and contribution to each area.

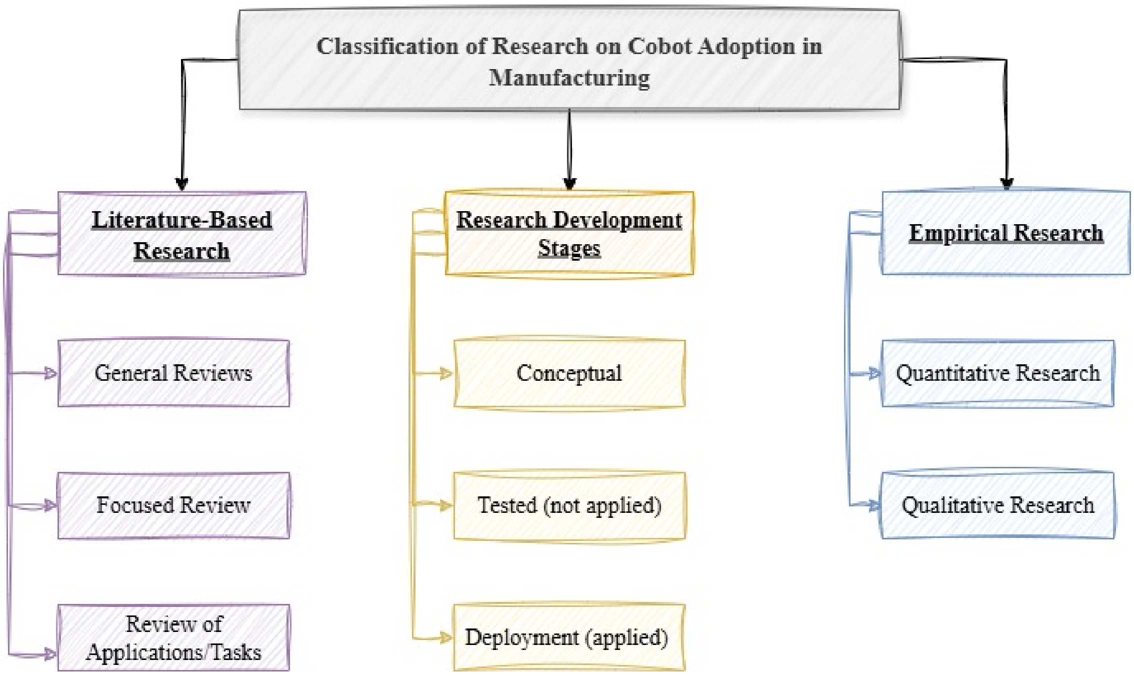

Figure 2.5 : Cobot Adoption in Manufacturing: Research Taxonomy

Literature-Based Research

The first category comprises literature-based research, represented by 10 literature review papers. Three types of reviews were identifed, as listed in Table 2.5, and discussed below.

Table 2.5 : Sub-Category of Literature-Based Research on Cobot Adoption in Manufacturing

Category	Related Paper
General Reviews	[22], [28], [29], [34], [41], [48]
Focused Reviews	[33], [42], [43], [53]
Reviews of Applications/Tasks	[22], [28], [29], [34], [48]

The first type of literature-based research is **general reviews**, with a total of six papers identified and discussed. This type offers a broad overview of the state of research across various manufacturing applications and cobot types, without focusing on specific aspects or applications/tasks. These reviews generally examine the benefits and challenges associated with cobots, as well as their application in industrial contexts. In terms of developing a broad taxonomy, two review papers addressed this topic. First, Segura et al. [34] proposed a taxonomy of components for cobots, involving four components: interaction level, communication interfaces, work roles, and safety control modes. This taxonomy generally provides a comprehensive framework that applies across various manufacturing fields and cobot types. Second, Hentout et al. [28] proposed a taxonomy of human-robot interaction system types (technical). This taxonomy is based on interaction types, control strategies, and system architectures. In addition, the authors discussed key challenges that may impede effective use, including safety concerns and cost issues, without focusing on a particular application or task involving cobots. These two taxonomies emphasise the technological components and interaction types that are used in practice, which differ from the taxonomy developed in this research, as it focuses on how and what type of research has been conducted in the manufacturing SME context. Therefore, the two aforementioned taxonomies and this current research taxonomy offer different but complementary perspectives that enhance the understanding of the cobot topic in the manufacturing sector. Another review offered a general overview of human factors in human-robot collaboration during operational use [41]. These factors include physical ergonomics (e.g., physical strain), mental workload, trust, acceptance and usability. Physical ergonomics and mental workload both affect operator well-being and task performance during collaboration activities. In addition, trust, acceptance, and usability are important elements that influence whether and how to adopt and interact with cobots. The most literature focus on cobot applications such as assembly processes and material handling (e.g., [22],[28],[29],[34],[48]), and machine tending (e.g., [28],[29],[34],[48]). Three studies focused on quality control (e.g., [28],[29],[34]). Two studies discussed cobot applications in welding operations and machining processes (e.g., [22],[34]), and disassembly operation (e.g., [22],[48]). This type of review reveals that two studies proposed taxonomies with a technical focus, while only one paper addressed human factors. However, there is a notable lack of attention regarding the role and applications of cobots within manufacturing SMEs.

Focused reviews represent another type of review, comprising a total of four papers. These reviews analyse the state of cobot usage in specific aspects or domains. To develop a specific taxonomy, De Simone et al. [44] developed a taxonomy focused on human factors (psychological) that influence cobot operator performance: stress, workload, trust, usability, and acceptance. In terms of various dimensions of relevant factors: first, a review by Cardoso et al. [33] focused on the importance of improving ergonomics as a requirement in human-robot collaboration. They identified two types of ergonomic evaluation factors: physical ergonomics, which includes body-related factors such as movement, physical stress, and muscle fatigue; and cognitive ergonomics, which involves mental workload, memory, and stress. Second, Silva et al. [43] proposed a set of decision-making criteria for cobot investment to support the decision process. These criteria include productivity, safety, flexibility, cost, programming, technical features, competitiveness, ergonomics, space, and mobility. Regarding another specific aspect regarding adoption risk and organisational readiness, Berx et al. [39] point out that safety issues, knowledge gaps, and regulations are critical barriers to cobot adoption. One key limitation of this type of review is that the taxonomy proposed by [44] remains in a preliminary phase. It lacks empirical testing, theoretical grounding in established human factor models, and validation. Further, only one study [33] applied SLR approaches, which would enable replication and further expansion of the research. Moreover, none of these reviews clearly address the practical applications of cobots and the context of manufacturing SMEs is notably absent.

The third category includes **reviews about applications** of cobots in the manufacturing sector. Five papers from the general review category were classified under this type. This separate grouping was included to enhance clarity about the application context rather than to replicate content. It may also support future development in taxonomy structure, particularly regarding use case differentiation between large manufacturers and SMEs. These papers reviewed applications/tasks in manufacturing where cobots could provide benefits in terms of productivity, safety and flexibility. Table 2.6 presents papers that examine the application uses of collaborative robots in manufacturing. Several applications for cobots are relatively more promising, offering several opportunities for further work to apply case studies on promising applications in manufacturing SMEs, an area that remains largely underexplored in the existing literature.

Table 2.6 : Papers on Cobot Application Uses in Manufacturing

Applications Fields Review	Related Paper
Assembly processes	[22],[28],[29],[34],[48]
Material handling	[22],[28],[29],[34],[48]
Machine tending	[28],[29],[34],[48]
Quality control/inspection/screening	[28],[29],[34]
Machining processes	[22],[34]
Welding operations	[22],[34]
Disassembly operations	[22],[48]

Research Development Stages

The second category, comprising the largest number of papers (16 in total), is associated with the research development stage. This category represents the natural progression of academic works from initial proposals, such as a model or concept, to practical implementation in a real-world context. Three separate stages were identified: the conceptual stage, the tested (not applied) stage, and the applied stage.

The conceptual subcategory comprised 7 papers. This stage of work focused on the early development and refinement of structured arguments to explain cobot adoption/use, and theoretical models or frameworks, with or without initial empirical exploration using qualitative methods to assess usability or perceived value. Table 2.7 details the contribution of each work within this stage. In the purely conceptual work, the authors primarily proposed theoretical models and discussed their potential benefits without a testing stage. These include: a conceptual maturity grid model for assessment of safety readiness [39]; the introduction of a paradoxical tension concept in cobot safety [42]; and a conceptual model that integrates UTAUT theory and soci-tecnnical system perspective to explore cobot acceptance in the Industry 5.0 context [40]. In the conceptual framework with qualitative evaluation, four papers [20],[24],[30],[37] developed models or tools and conducted initial empirical qualitative methods. Among these, only 3 papers focused on assembly processes, and on welding operations.

Table 2.7 : Studies at the Conceptual Stage of Cobot Implementation in Manufacturing

Paper	**Process**	**Description/Contribution**
[20]	Welding operations	A qualitative exploration of organisational human factors: A case study at a UK aerospace manufacturer.
[24]	Assembly processes (only mentioned in two companies)	Development of the integrated DOI–TOE–INT framework through qualitative research involving six companies.
[30]	Assembly processes	Qualitative study employing Grounded Theory methodology with assembly workers.
[37]	Assembly processes	Development of a web-based tool for employee acceptance. Preliminary validation based on a qualitative study.
[39]	N/A	Conceptual maturity grid model (CSRAT) for system-wide safety readiness assessment.
[42]	N/A	Identifies paradoxical tension in cobot safety where robots appear simultaneously "too safe" (limiting productivity), "inherently safe" (from a technical perspective), and "less safe" (from a system-wide perspective). This confusion contributes to low adoption rates.
[40]	N/A	Conceptual model integrating UTAUT and STS theories for cobot acceptance in manufacturing environments.

The tested stage subcategory is the second within the development stage, and is the largest, comprising a total of 8 papers. This stage includes studies that examine cobot adoption and/or usage models or methodologies through experiments, simulations, or user data collection, without consistent deployment in real-world industrial settings (Table 2.8). Among these, only two papers focused on assembly processes and two papers on machine tending activities.

Table 2.8 : Studies at the Tested Stage of Cobot Implementation in Manufacturing

Paper	**Application/Task Category**	**Description/Contribution**
[27]	Material Handling (pick and place operations, packaging)	Feasibility study validated via empirical monitoring, digital twin simulation, and Monte Carlo analysis.
[21]	Assembly processes (component monitoring, fastening operations)	Empirical validation of human-robot collaboration acceptance model through a cross-cultural survey.
[32]	N/A	Empirical validation of success factors for industrial human-robot interaction via an online survey of German manufacturers.
[54]	N/A	Empirical validation of TOE-DOI framework via SEM with Chinese SMEs.
[36]	N/A	Empirical validation of sociotechnical factors via SEM with Russian manufacturing firms.
[47]	Assembly process	Theoretical cost model developed and empirically validated with real manufacturing case studies. Tested with industry data, though no cobot systems were implemented.
[23]	Not identified	Empirical validation of TOE-DOI-INT framework via SEM with Portuguese companies.
[49]	Machine tending (loading/unloading plastic components)	Collaborative project between Polytechnic University and TechPol Srl, an SME, to use cobot technology for welding station automation. Reported 86% reduction in worker time.

The third subcategory is the applied stage, which includes studies that successfully deployed cobots in industrial settings. A total of three case study papers were identified in this subcategory (see Table 2.9). This stage enables direct observation of cobot performance and real integration with operational work. Two of the case studies focused on material handling and one on assembly tasks.

Table 2.9 : Studies at the Deployment (Applied) Stage of Cobot Implementation in Manufacturing

Paper	Application/Task Category	Description/Contribution
[31]	Assembly process	Demonstrates real-world deployment of a human-robot collaboration system in aerospace manufacturing, achieving a 25% reduction in assembly time and a 30% reduction in non-recurrent costs.
[35]	Material handling (picking and placing operation for food packaging)	Demonstrates real-world deployment of a cobot system in an industrial kitchen, achieving a 23% cost reduction, acceptable payback period, and measurable ergonomic improvements.
[45]	Material handling (pick and place operations)	Industrial deployment of an interactive cobot programming method enabling rapid setup and non-expert operation.

Empirical Evidence on Factors and Barriers to Cobot Adoption

The third category of research on cobots in manufacturing comprises empirical studies that investigate the factors that drive and/or hinder cobot adoption. A total of 14 papers were identified in this category (Table 2.10). As shown in Table 3, notable variations exist in the research context and study design, including differences in sample and participant profiles. Germany was the most frequently represented context, appearing in 6 papers. Regarding company size, five papers did not specify, three mentioned a mix of large companies and SMEs, two focused on large companies, and four focused on SMEs. Among these studies, a qualitative research design, such as interviews, workshops, and open-ended surveys, were used in eight papers, and quantitative surveys were employed in six studies. The studies also differ in their examination of factors and barriers. There is an increased interest in investigating these factors or barriers in general. In the section on barriers to adoption and adoption factors, the difference between each factor category will be presented.

Table 2.10 : Empirical Studies on Cobot Implementation in Manufacturing

Paper	Study Context	Method & Sample	Factors	Barriers
[20]	UK (Large)	Qualitative (interviews). Participants (n=12; roles included operators, technical/management.	✓	✓
[25]	South Africa	Qualitative (Survey with open-ended questions). Participants (n=12) roles included IT managers and production managers.	✓	✓
[15]	Spain (Mixed: large, SME, students)	Early stage qualitative study (workshops, questionnaire). Professionals (n=51) and vocational training students (n=38).		✓
[26]	Finland	Quantitative (online questionnaire). Participants (n=75) from industry, academia, integrator and distributor.		✓
[21]	Germany, Japan, China, USA	Quantitative (large-scale cross-cultural survey).Participants (n=1362); roles included operational production workers.	✓	

Continued on next page

Table 2.10 (continued)

Paper	Study Context	Method & Sample	Factors	Barriers
[24]	Portugal and France (Large)	Qualitative (interview). Participants (n=13) from 6 companies; roles included managers.	✓	
[30]	Germany	Qualitative (interview). Participants (n=17) from 4 companies; roles included assembly workers.	✓	
[37]	Germany (SMEs)	Qualitative (tool development). Participants (3 SMEs with five managers for evaluation).	✓	
[32]	Germany (Mixed: large and SMEs)	Quantitative (Survey). Participants (n=81); roles included managers and technical/production personnel.	✓	✓
[54]	China, Guangdong (SMEs)	Quantitative (Survey). Participants (n=242); roles included managers.	✓	
[36]	Russia, Moscow (unspecified)	Quantitative (Survey). Participants (n=351) from 10 companies; roles included management staff.	✓	

Continued on next page

Table 2.10 (continued)

Paper	Study Context	Method & Sample	Factors	Barriers
[38]	Sweden (SMEs), Hungary, Germany	Qualitative (Interview). Participants (n=8) from 5 Swedish SMEs and (n=3) international firms; roles included managers, engineers and operators.		✓
[46]	Italy, Germany, Finland (SMEs)	Qualitative (Interview). Participants (n=5) from 5 SMEs; roles included decision makers (e.g., CEO).	✓	✓
[23]	Portugal (SMEs)	Quantitative (survey). Participants (n=78) from 5 SMEs.	✓	

Some important observations emerge from this systematic review. On the positive side, cobot adoption and its applications in manufacturing environments are progressing. The reviewed studies include a wide range of cobot uses and applications across various manufacturing domains. There is also evidence that cobots are deployed/applied for various purposes and solutions; however, the number of related studies remains very small, at only three. In contrast, 11 papers focused on the tested stage, indicating growing interest among researchers in developing and testing models. Yet, this stage generally remains limited. Importantly, only four papers focused extensively on the SME context [23, 37, 46, 54] but they lack clear, explicit details about the specific cobot application/task that was evaluated. In addition, these studies differ significantly in their methods, samples, and the factors or barriers being studied. Overall, research remains unclear on the application of and the factors/barriers to cobot adoption, particularly in manufacturing SMEs, which may cause SMEs to remain cautious.

2.3.2 Cobots Adoption in Manufacturing: Reasons

This section presents the reasons that motivate manufacturing environments to adopt cobots, as highlighted by research papers [22],[25],[27],[28],[29],[30],[31],[32], [41],[43],[45],[47],[48],[49]. The reasons stem from problems commonly associated with the need to transition to cobot adoption/use. The specific reasons for adoption cobots in manufacturing environments are presented in Figure 2.6.

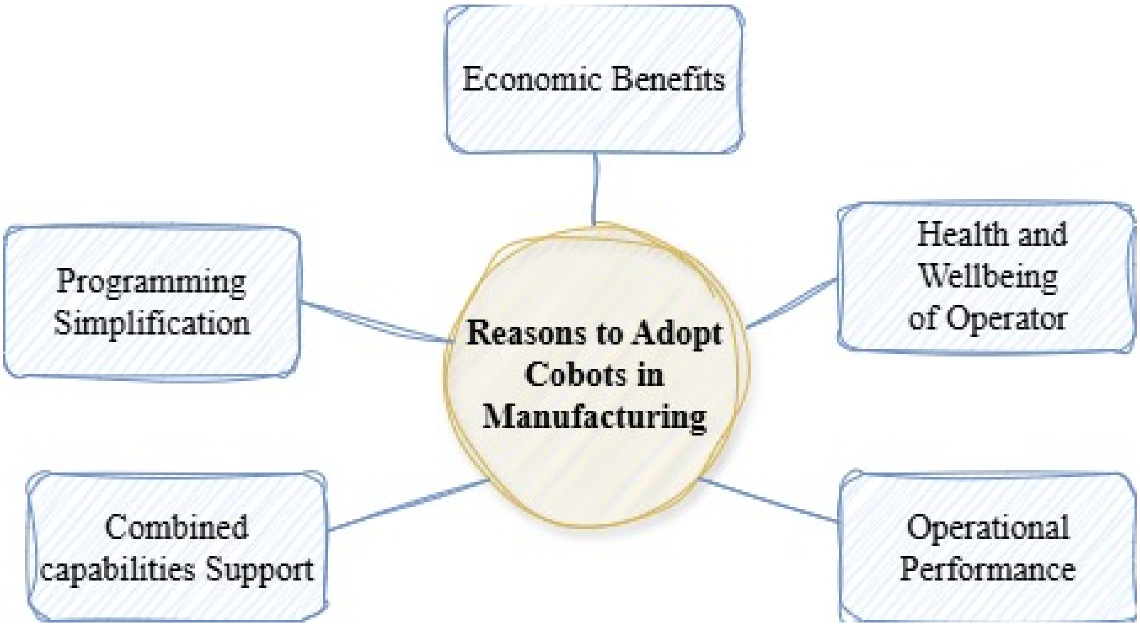

Figure 2.6 : Reasons to Adopt Cobots in Manufacturing

Economic Benefits are a major reason for the use of cobots, as manufacturers seek ways to enhance efficiency and increase return on investment (ROI). Cobots can reduce operational expenses due to their easier integration and smaller size compared to traditional industrial robots [30],[48],[49]. Labor costs can be reduced by using cobots in industrial processes, as they lower the number of operators required through the automation of repetitive tasks, such as packaging operations [27],[45]. For SMEs, cobots are particularly suitable due to their flexibility and ease of programming, which allow for small lots and facilitate product changes at a lower cost [25],[32]. Further, cobots reduce the need for safety infrastructures. Given this benefit, humans and robots can work together without fencing [45], a novel feature compared to traditional industrial robots. Finally, cobots help maintain market competitiveness based on their ability to provide highly customized small-batch production and rapid adaptation to customer requirements [45],[49].

Some benefits of using cobots in manufacturing fall into **operational performance** in terms of responsiveness and capability. Cobots help deliver time and speed improvements by reducing disruptions and optimising manufacturing processes [49]. Process efficiency is achieved by reducing waste and strategically allocating resources between robots and humans [22],[27],[31],[47]. Further, cobots support factory space optimisation without requiring major changes to the existing floor layout [43].

Regarding the advantages related to the **health and well-being of operators**, researchers highlight the importance of enhancing and safeguarding their physical and mental health. Cobots can support long-term operator performance by reducing continuous fatigue associated with intensive tasks [43] and preventing musculoskeletal disorders by reducing high-strain manual operations [43]. Safety features such as safety-related monitor stop functions and advanced sensors help mitigate accident risk in collaborative workspaces [28],[29].

Programming simplification of cobots offers advantages that reduce the effort and expertise required for coding. One example is interface-based programming, which uses user-friendly interfaces to enable easy setup [43],[49]. Another is the capability of learning by demonstration, where workers physically guide the robot to perform tasks, without the need for coding [29].

Finally, one of key reasons for using cobots is the enhancement of tasks through the**combined capabilities of humans and robots**. This includes human intelligence with robotic accuracy, human adaptability with robotic strength, and human dexterity with robotic consistency [28].

2.3.3 Barriers

The review identified several barriers to cobot adoption in manufacturing, as outlined in Table 2.11, with empirical and review findings presented in separate columns. To enhance clarity and avoid repetition of conceptually similar terms described differently by researchers, these barriers are grouped into a single row where appropriate. Four barriers were most frequently mentioned by researchers. Safety was considered the most significant challenge to cobot adoption [15],[26],[28],[38],[39] [46]. Researchers highlighted various legal and safety issues [28], performance limitations arising from safety constraints [38], and safety-related concerns stemming from perceived risks and the need for thorough safety assessments [46]. Another major barrier identified is a lack of knowledge, often linked to limited experience and a shortage of skilled employees [15],[25],[26],[42],[46]. Fear of job loss was frequently identified as a major barrier, often associated with retrenchment or displacement due to automation [25],[46] and resistance behaviour resulting from fear [32]. In these studies, the barrier was identified through insights of managers and technical experts. Further, Cost-related issues emerged as one barrier to cobot adoption [15],[26],[43], encompassing challenges such as high initial investment and complex cost-benefit evaluations [43]. Other barriers were highlighted less frequently by researchers, such as acceptance/skepticism [15],[46], lack of union communication, limited resources for automation development, resistance from unions [20], technical limitations (cobot technical properties) and issues with system integration [26], performance constraints (issues related to cobot features: speed, time, and quality of work), involvement challenge, and strategic concerns [38]. Overall, it can be concluded that certain barriers remain underexplored, highlighting the need for further empirical studies to investigate these barriers and uncover emerging challenges that may hinder cobot adoption, particularly in SMEs.

Table 2.11 : Barriers to Cobot Adoption in Manufacturing

Barriers	**Empirical**	**Review**	**Barriers**	**Empirical**	**Review**
Safety issues	[15],[26],[38] [46]	[28],[42]	Lack of knowledge/lack of Integration knowledge	[15],[25],[26],[46]	[42]
Cost issues	[15],[26]	[28],[43]	Fear of job loss	[25],[32],[46]	
Lack of union communication	[20]		Acceptance/Skepticism	[15],[46]	
Resistance from unions	[20]		Technical limitations	[26]	
Resources for automation development	[20]		Lack of system integrators	[26]	
Job redesign	[46]		Performance limitations	[38]	
Involvement challenge	[38]		Strategic issues	[38]	

2.3.4 Factors Influencing Adoption

Understanding the determinants of adoption is essential for the effective implementation of cobots, as it allows decision-makers to anticipate and mitigate potential barriers to their adoption. Through the analysis and validation of data from the selected papers, factors influencing adoption were identified. These determinants were derived from empirical, conceptual, and review studies, and subsequently classified into human dimensions (both individual and organisational characteristics), environmental, organisational, and technological, as shown in Table 2.12. Two important notes apply to these classifications. First, a few papers adopted frameworks that supported factor classification [23],[24],[54]. In this study, all factors were grouped under the major categories of technological, organisational, and environmental, with human factors added as an additional category to capture a wide range of elements related to human aspects. As shown in 2.12, some factors were combined into a single row where they were conceptually related, thus avoiding unnecessary repetition. For example, complexity and ease of use, as well as trialability and pilot project were grouped together. According to Venkatesh et al. [55], factors with similarities in meaning and application (e.g., complexity and perceived ease of use) can be combined to enhance clarity in analysis; this study adopted the same approach. Second, human factors were divided into two subcategories. The individual subcategory relates to personal attributes, capabilities and perceptions of individuals, such as behaviour, prior knowledge and trust. The organisational-human subcategory refers to people or roles within an organisation that influence adoption and implementation by shaping employees' willingness and ability to engage with the technology. This influence encompasses organisational processes such as communication of change, support and the existence of a champion. This subcategory was identified by Charalambous et al. [20] and was therefore retained in this study as a distinct subset of human factors. For example, while certain factors, such as management support, can be viewed as organisational mechanisms when considered from a structural or resource allocation perspective, the same factor, senior management support, has been classified by researchers [20] as an organisational human factor when linked to employees' acceptance and motivation. In this study, such factors were retained under the category assigned by the primary study authors to ensure consistency with the perspective adopted in the primary research and maintain conceptual integrity. Overall, some concepts are relevant to more than one domain; therefore, human factors are considered not only as individual elements, but also in terms of their interaction with organisational processes, enabling a clear representation of adoption factors as presented in the literature.

Table 2.12 : Factors Related to Cobot Adoption in Manufacturing

Factors	**Empirical**	**Conceptual**	**Review**	**Factors**	**Empirical**	**Conceptual**	**Review**
Technological Factors							
Complexity/Ease of Use	[21],[24],[46],[54]		[28],[43]	Relative Advantage/Usefulness	[21],[23],[24],[36],[54]		
Trialability/Pilot Project	[24],[46][54]			Technical Features	[24],[30]		[43]
Observability	[24],[54]			Compatibility	[23],[24],[54]		
Dependability /Reliability	[25],[30]			Safety	[30],[32]		[43]
Technical Subsystem	[36]	[40]		Output Quality	[21]		
Support	[24]						
Organisational Factors							
Top Management Support	[22],[23],[24],[36]			Organisational Readiness	[24],[54]		
Work Design	[36]	[40]		Financial Costs	[32]		
Receptiveness	[24]			Project Champion	[24]		

Factors	**Empirical**	**Conceptual**	**Review**	**Factors**	**Empirical**	**Conceptual**	**Review**
Technological Infrastructure	[24]			Relationships (Executive/Colleagues)	[30]		
Training	[36]			Implementation Process	[30]		
Competitiveness			[43]	Incentives	[36]		
Facilitating Conditions		[40]		Corporate Culture	[37]		
Vision	[46]			Work Routine Change	[37]		
Resources	[23]			Open Innovation	[46]		
				Human Resources	[23]		
Environmental Factors							
Competitive Pressure	[22],[24]			Industry Pressure	[23],[24]		
Communication	[25]			Government Agencies	[24]		

Factors	Empirical	Conceptual	Review	Factors	Empirical	Conceptual	Review
Financing Agencies	[24]			Government Support	[54]		
Business Partners	[24]			Vendor Support	[54]		
Human Factors – Individual							
Trust	[25],[30],[32]		[33],[41],[44]	Acceptance			[33],[44],[41]
Prior Experience /Knowledge	[30],[36],[37]			Usability			[33],[44],[41]
Perceived Safety	[21],[37]			Negative Feelings	[21],[30]		
Positive Feelings	[21],[30]			Technology Affinity	[21],[37]		
Subjective Norm/Social Influence	[21]	[40]		Perception of External Control	[21]		
Job Relevance	[21]			Self-Efficacy	[21]		
Image	[21]			Demonstrability	[21]		
Perceived Risks	[30]			Self-Assessment	[30]		

Factors	Empirical	Conceptual	Review	Factors	Empirical	Conceptual	Review
Perceived Benefits	[30]			Innovativeness	[36]		
Effort Expectancy		[40]		Performance Expectancy		[40]	
Human Factors–Organisational							
Communication of the Change	[20]			Flexibility through participation	[20]		
Existence of a Champion	[20]			Workforce Training	[20]		
Operator Participation	[20]			Senior Support	[20]		
Social Subsystem	[36]						

As discussed, some factors were grouped into a single row, and this was clarified by the researcher during the presentation of the results. Within the **technological dimension**, some factors were identified across empirical and conceptual/review papers, each with varying influences on cobot adoption. The first factor, complexity, had a significant negative influence on adoption [22], while ease of use had a strong positive effect [21]. Qualitative findings described complexity as low [24] but also identified it as a technical barrier [46]. It was also reported in review works [28],[43]. The effect of relative advantage/usefulness was found to be strongly positive in some studies [21],[54], negative in one study [36], and nonsignificant in another [23]. A qualitative study identified it as an important factor [24]. The trialability factor showed a strong positive effect [54]. In two qualitative studies, it was identified as an enabling factor [46], and work in [24] identified it as a technology factor. Technical features were cited in qualitative research. One study [30] discussed them in terms of process and cobot design as prerequisites for cobot acceptance. Another study by [24] highlighted these factors in relation to task execution speed and probability, identifying them as important considerations. They were also mentioned in review work [43]. Observability and compatibility were found to have a strong positive effect in one study [54] but were deemed nonsignificant in another [23]. A qualitative study by [24] identified these two factors as important. Dependability/reliability was identified as an important factor in two qualitative works [25],[30]. Safety was identified as a success factor involving hazard identification and risk assessment [32], and was determined to be a priority factor in a qualitative study by [30], and in a review paper [43]. The technical subsystem factor was found to have a positive effect in [36], and was also mentioned in conceptual work [40]. Furthermore, output quality had a positive effect [21], and support was mentioned as a factor in qualitative work in [24].

The organisational dimension was the second category and included several factors of varying importance. Top management support was identified as a relevant determinant in [22],[23] and [36], and was also highlighted as important in qualitative work [24]. Organisational readiness was also an important determinant in [54] and as an important factor in a qualitative study [24]. Work design was found to have a non-significant effect in [36], but was cited as a relevant factor in conceptual work [40]. Other determinants, such as financial cost, were rated as moderately relevant for the effective adoption of cobots [32]. Receptiveness, project champion, and IT infrastructure were found to be important factors in cobot adoption [24]. Further, training was identified as a positive factor in [36]. In qualitative work, the implementation process was presented as a critical factor influencing human-robot acceptance [30]. The incentive factor was found to have no effect [36]. Corporate culture and work routine changes were determined as theoretical components of their cobot acceptance assessment tool in a qualitative study [37]. In [23], resources were identified as a positive factor while human resources had no effect. Moreover, open innovation was presented as an enabler [46], competitiveness was highlighted in review work [43], and facilitating conditions were emphasised in conceptual work [40].

Within the **environmental dimension**, several factors were identified across empirical studies. Competitive pressure showed no effect [22], whereas one qualitative study identified it as a strong enabler [24]. Industry pressure was found to have a positive effect [23], and was also recognised as a strong enabler in qualitative research [24]. In other qualitative work, communication was identified as the key factor [25]; government agencies and business partners were recognised as strong enablers, while financing agencies were considered moderate enablers [24]. Government support and vendor support showed no effect [22].

The human dimension was presented in two subcategories: individual and organisational human factors. First, individual factors included those identified in empirical, conceptual, and review studies. Trust was rated as an important factor [32], identified as key factor in two qualitative studies [25],[30], and mentioned in three review papers [33],[41],[44]. Prior experience had a positive effect [36], and in qualitative studies, was perceived as an important factor [30],[37]. Acceptance and usability were mentioned in three review papers [33],[41],[44]. Perceived safety was also a strong positive factor [21], and, in qualitative work [37], was identified as an important factor. Negative feelings such as anxiety had a negative effect [21], and qualitative studies identified anxiety alongside feelings of uncertainty, helplessness, worthlessness or frustration as a primary factor of importance [30]. Positive feelings such as enjoyment had a strong positive effect [21]. In a qualitative study, enjoyment, alongside feelings of curiosity and excitement, was perceived as a primary factor of importance [30]. Technology affinity was identified as a negative factor in [21], while in qualitative work, it was perceived as significant, with both positive and negative potential [37]. Innovativeness was identified as a positive factor in [36]. In the work by [21], subjective norm had a positive effect and was also mentioned in conceptual research [40]. Further, perception of external control and job relevance were strong positive factors. Five other factors: image, self-efficacy and result demonstrability had moderate positive effects [21]. Other factors, such as result demonstrability, had a strong effect [21]. Perceived risk, perceived benefits, self-assessment, and work motivation were considered primary influencing factors [30]. Effort expectancy and performance expectancy were highlighted in a conceptual paper [40].

Second, organisational human factors were identified through an empirical study. In work by [20], six enabling factors were highlighted: operator participation, existence of a champion, communication of the change, senior management support, training, and flexibility through participation. Furthermore, in the work by [36], the social subsystem, which includes group culture, relationships, and social dynamics, was found to have no effect.

Following the analysis of the review findings, four main dimensions were identified: technological, organisational, environmental and human, with one additional social dimension, as presented in Table 2.12. The table presents an initial map that includes these dimensions and their related factors, extracted from empirical, conceptual, and review papers. Importantly, the majority of factors are supported by only one or two studies in each dimension, and some are highlighted exclusively in conceptual or review papers. This suggests that current evidence is insufficient to confirm the relative importance of these factors in adoption. Additionally, the distribution of factors varies: with some studies emphasising human factors at the individual level, while technological and environmental dimensions have received comparatively less attention. Only four studies focused on SMEs. One focuses on individual factors [37], another study highlighted only a small subset of technological and organisational factors [46], and two addressed a different subset of technological, organisational and environmental factors [54], but [23] did not provide full coverage. Therefore, further empirical studies on manufacturing SMEs that investigate the main dimensions as a holistic framework for adoption decisions are required. For the most part, decision-makers are responsible for choices related to new technologies, including their trial and adoption in industry. Therefore, a comprehensive map of influencing factors can support more informed adoption decisions. This highlights a significant aspect for improvement in future investigations, particularly since the somewhat low adoption rates in the manufacturing SME context.

To provide a cross-context synthesis of the most influential empirical evidence, Table 2.13 summarises key studies that have significantly shaped understanding of adoption factors across different manufacturing and digital technology contexts.

Table 2.13 : Summary of Influential Empirical Studies on Adoption Factors Across Contexts

Study	**Context**	**Technology**	**Key Adoption Factors Identified**
[56]	SMEs	Cloud computing	Relative advantage, compatibility, complexity, top management support, competitive pressure
[57]	SMEs	B2B e-commerce	Relative advantage, organisational readiness, firm size, competitive pressure
[58]	Manufacturing firms	Smart manufacturing technologies	Digital knowledge, strategic alignment, perceived value, environmental pressure
[59]	Manufacturing organisations	IIoT	Relative advantage, organisational readiness, vendor support, security concerns
[60]	Manufacturing SMEs	Industry 4.0	Compatibility, complexity, top management support, market uncertainty
[24]	Manufacturing firms	Collaborative robots	Relative advantage, compatibility, trialability, management support, regulatory environment
[54]	Industrial organisations	Collaborative robots	Relative advantage, organisational readiness, vendor support, government support
[61]	Organisations	Generative AI	Relative advantage, compatibility, absorptive capacity, competitive pressure

2.3.5 Theory/Model/and Framework in Cobot Adoption

Theoretical frameworks of adoption presented in this study were very limited, involving only five empirical works and one conceptual study, none of which have yet been evaluated, as shown in Table 2.14. From the perspective of theoretical technology adoption: at the organisational level in large manufacturing (as classified in Table 2.10) [24], the DOI-TOE-INT framework was applied. In manufacturing SMEs [23], the DOI-TOE-INT framework was also used; while another SME study [54] applied the DOI-TOE framework. At the individual level, Broeh et al. [21], applied the TAM and its extensions. Furthermore, the review identified another perspective, namely a sociotechnical perspective in one empirical study [36] and the UTAUT combined with STC in one conceptual study [40].

In general, sociotechnical perspectives focus on change processes or actual use rather than adoption determinants (intent to adopt) [40]. In the work by [36] , as discussed above, limited effectiveness was found when applying sociotechnical factors as adoption determinants. Only one of three factors (technical subsystem) showed a positive effect, while work design and social subsystems had no effect. Therefore, from this perspective, the ability to explain or predict adoption intent is limited.

As such, among the limited works available in literature, particularly at the organisational level in empirical studies, DOI and TOE were the dominant frameworks, with only two studies conducted in the SME context. However, it is clear these two studies did not consider human factors. In summary, the theoretical development of surrounding cobot adoption in manufacturing SMEs is still in its early stages and provides valuable opportunities as a foundation for future work.

Table 2.14 : Theories and Models Relevant to Cobot Adoption

Paper	Theory/Model	Type	Category	Factors Considered
[21]	TAM-TAM2-TAM3	Empirical	Individual-Based	Technological (3 factors), Human (Individual) (12 factors)
[24]	DOI-TOE-INT	Empirical	Organisational-Based	Technological (7 factors), organisational (5 factors), environmental (5 factors)
[54]	DOI-TOE	Empirical	Organisational-Based	Technological (5 factors), organisational (2 factors), environmental (3 factors)
[36]	STC, with some organisational & individual factors	Empirical	Socio-Technical	Human (individual factors), organisational (1 factor), social-technical factors (3 factors)
[40]	UTAUT-STC	Conceptual	Individual & Socio-Technical	Human (individual factors), organisational (2 factors), social-technical factors (3 factors)
[23]	DOI-TOE-INT	Empirical	Organisational-Based	Technological (2 factors), organisational (3 factors), environmental (2 factors)

2.4 Gaps in the Literature

This SLR identified several gaps:

- Existing works on cobot adoption primarily focus on large firms and, in some cases, do not specify firm size. This highlights a possible gap in the literature concerning the distinct adoption factors, challenges, and decision-making processes relevant to the SME context. Organisational capabilities and resource constraints in SMEs differ significantly from those in larger firms; however, this distinction has received limited attention.

- While the existing literature has identified certain factors influencing cobot adoption, current research presents a partial understanding, lacking a comprehensive examination of both facilitating and inhibiting factors within a unified analytical framework. This potential gap is particularly evident in the context of manufacturing SMEs, where holistic insights remain scant and require systematic integration.

- Although only two studies have presented theoretical frameworks for cobot adoption in manufacturing SMEs, these frameworks demonstrate limitations in sufficiently integrating human factors and barriers with technological, organisational, and external factors as specific influencing dimensions within their theoretical model to understand the adoption process in this organisational context.

- Based on the literature, among the 14 empirical studies reviewed, only two were qualitative investigations [37],[46] and two were quantitative studies [23],[54] on cobot adoption in manufacturing SMEs. These studies exhibit several limitations, including small sample sizes in some cases, a primary focus on managerial perspectives with limited or no consideration of technical experts' perspectives, despite their important role in technology adoption decisions, and, in some cases, a lack of validation and generalisability of the findings. To address these limitations, employing mixed-methods approaches that combine quantitative and qualitative data represents a useful direction for further work, achieving a better understanding of this context and incorporating different perspectives from management-level and IT experts.

- To the best of the authors' knowledge, no existing study has examined cobot adoption in Oceania, particularly among Australian manufacturing SMEs. Given Australia's unique industrial structure, high labour costs, and ongoing skill shortages, understanding this context, particularly in manufacturing

SMEs, is crucial. With growing global interest in this topic, particularly in Western countries such as Germany, France, and Portugal, research in the Australian context is essential for building knowledge that can benefit both local industry and the broader international community.

Regarding the identified gaps in the current review on cobot adoption in manufacturing SMEs, there is a request for a thorough exploration of factors and barriers that influence the adoption process within this context. These factors require clear dimensional classification and organisation to enhance analytical consistency and theoretical clarity. Based on the review undertaken, a detailed analysis and classification of the identified barriers (Table 2.11) and influencing factors reported in existing studies (Table 2.12) were conducted. Further analysis of the existing theoretical frameworks of adoption (Table 2.14) reveals that current theoretical frameworks determine adoption at the individual and organisational levels and show that only two frameworks at the organisational level have been applied at SMEs [23],[54]. Therefore, the researcher synthesised these findings to develop a comprehensive classification system that involves five major dimensions: technological, organisational, environmental, human and barriers (Table 2.15). This table presents all 14 empirical studies. It is evident that organisational-level frameworks, such as TOE and DOI, tend to overlook human factors and barriers as specific contextual dimensions, whereas studies not based on theoretical frameworks occasionally consider these aspects. This clearly demonstrates the need for a consistent and comprehensive understanding of the topic through the lens of the five dimensions. Accordingly, this study identifies these five dimensions as important to understanding and influencing the cobot adoption process in manufacturing SMEs.

Table 2.15 : Summary of Theoretical Frameworks and Related Dimensions in Cobot Adoption Research

Paper	Theory/Model	Adoption-Related Dimensions				
		Technological	**Organisational**	**Environmental**	**Human**	**Barriers**
[20]	N/A				✓	✓
[25]	N/A			✓	✓	✓
[15]	N/A					✓
[21]	TAM,TAM2,TAM3	✓			✓	
[26]	N/A					✓
[24]	DOI-TOE-INT	✓	✓	✓		
[30]	N/A	✓			✓	
[37]	N/A	✓			✓	
[32]	N/A	✓				✓
[54]	DOI-TOE	✓	✓	✓		
[38]	N/A					✓
[46]	N/A	✓	✓			✓
[36]	STC, with some organisational and individual factors	✓	✓		✓	
[23]	DOI-TOE-INT	✓	✓	✓		

2.5 Limitations of this SLR

Several limitations should be taken into account in this systematic review. One such limitation involves the range of databases used for literature extraction. Although it is practically difficult to screen all available sources due to time constraints, the databases selected were chosen for their recognised academic credibility and comprehensive coverage. As such, they offer a representative selection of research on cobot adoption. In addition, a practical and established screening protocol was applied to evaluate the literature systematically, helping to reduce potential selection biases in the review process. Another limitation is related to the rapidly evolving nature of technological advancement in the manufacturing sector. Given the rapid evolution of cobots and their integration into SME operations, the results of this review may require future updates to remain current. Nevertheless, this review offers a valuable baseline for comparing the present state of cobot adoption with future developments, enabling the tracking of technological progress and the practical and theoretical advances it brings to manufacturing SMEs. Finally, the conclusions of this review are influenced by the researcher's subjective views of the existing literature. It is important to clarify that the aim was not to measure the current extent of cobot adoption in manufacturing settings or to evaluate its adoption status. Instead, the objective of the study was to systematically review the existing body of knowledge on cobot adoption and to identify areas where further research is needed. In this regard, the findings provide a useful basis for guiding future empirical investigation in this field.

2.6 Summary

Chapter 2 offers a comprehensive overview of the current research related to cobot adoption in manufacturing. A taxonomy was developed drawing on the analysis of 32 papers, providing a well-organised summary of the present body of knowledge The shortlisted papers were classified into three categories: literature-based research (including overviews and cobot applications), research development stages (conceptual, tested but not applied, and implemented or operational in real-world contexts), and empirical research (identifying factors and barriers related cobot adoption). Existing review papers that discuss taxonomies focus on various aspects of the topic. For example, [28] classified cobot literature by research topics such as hardware design, safety, programming approaches and task allocation. [34] developed a system design for a cobot, and [44] determined human performance aspects in collaboration, such as stress, workload, usability, and acceptance. The current taxonomy developed in this study provides a complementary view by focusing specifically on the progression of cobot adoption research in manufacturing SMEs. It contributes to the field by systematically classifying adoption barriers, factors, and theoretical frameworks/models relevant to the manufacturing SME context. This taxonomy helps to determine research gaps in cobot adoption works and provides direction for future studies where further development is needed.

The literature indicates a growing research interest in cobot adoption in manufacturing environments. Although empirical investigations are beginning to emerge, with 14 papers studying aspects of adoption, research on this topic remains in its early stages, marked by ongoing theoretical and practical development.

This review reveals several avenues for future investigation. First, the literature includes six empirical studies that apply quantitative methods and seven that use qualitative methods. However, several methodological limitations exist regarding sample size representativeness, the rigour of methodological execution, and the generalisability of the findings. Accordingly, a case study that employs mixed methods (quantitative and qualitative) enables the acquisition of contextual insights by integrating practical knowledge from key stakeholders, such as managerial staff and technical personnel, with academic research, while also supporting the findings with measurable data relevant to adoption factors and barriers within a unified study framework. In addition, action research can provide collaboration with stakeholders and help link practical experience to research. This review identified only three empirical studies using technology adoption models/theories: three at the organisational level, and one at the individual level. Furthermore, another study used a sociotechnical perspective. Of these, only two studies address organisational adoption in SMEs, highlighting the limited theoretical development in understanding the cobot adoption process in manufacturing SMEs. Finally, an important gap exists in the lack of a holistic approach to cobot adoption that empirically investigates five different dimensions of factors among manufacturing SMEs. There is no holistic model, to the best of the author's knowledge, that currently exists for Australian manufacturing SMEs. As a result, additional studies are required to develop a holistic framework specifically for manufacturing SMEs, which can serve as a robust basis for future empirical works. Chapter 3 presents the research questions, subquestions, and objectives based on the identified research gaps.

Chapter 3

Problem Definition

3.1 Overview

Chapter 3 provides the research problem. The main concepts utilised in the current work are defined in section 3.2, and the key research questions are specified in section 3.3. The objectives of this work are also outlined in section 3.4

3.2 Key Terms and Concepts

A list of the key concepts and terms utilised in this research:

Collaborative Robots: Collaborative robots (cobots) are among the most advanced robotic innovations implemented in both industrial and service sectors. This research focuses on cobot adoption in industrial settings. Unlike industrial robots, cobots can work with humans in a shared workspace without safety fencing, thus enhancing productivity and safety in the industrial context [31].

Manufacturing SMEs: Manufacturing refers to a process that includes transforming raw materials into final products that can be sold in the market [62]. Manufacturing SMEs, namely companies or firms, are smaller than large firms with respect to assets, number of employees or turnover. These SMEs vary from country to country or among groups of countries such as the European Union. This study utilises the definition outlined by the Australian Bureau of Statistics (ABS), which determines SMEs as organisations with 1-99 employees [9].

Holistic Framework: This is a comprehensive, integrative approach to addressing problems or making decisions that consider all the related factors and aspects to achieve a unified comprehension of a particular context. This approach focuses on the whole part rather than a single one to gain an accurate perspective that accounts for the relationships between different variables and the interconnections. This, in turn, provides a complete conclusion or solution.

Technological Factors: These are the features or properties influencing the use and adoption of a particular technology. Guided by the Diffusion of Innovation (DOI) theory [63], the study utilises the five attributes of innovation as the technology factors.

Organisational Factors: These are the intra-organisational features and dynamics that can influence the structures, performance and operation of an organisation or firm, its capability to accomplish objectives and goals, and its capability to adapt to change. Within technology adoption, organisational factors serve a main function in assessing the suitability of a particular technology for the organisation. Guided by the Technology–Organisation–Environment (TOE) framework, this research specifies the primary organisational determinants influencing adoption [4].

Environmental Factors: These are the entities, processes and systems that shape the broader setting of organisational functions. Although environmental factors impact organisations, they do not exert direct authority over them. Several examples include the national and political environment, market conditions and competitors. Based on the Technology-Organisational-Environment (TOE) framework, this research highlighted the primary environmental determinants influencing technology adoption [4].

Human Factors: In the current study, human factors are viewed as a broad concept that includes both individual and organisational attributes, roles, and capabilities that may influence cobot adoption. Individual human factors focus on personal attributes that may affect the willingness of a person to adopt and use cobots [64]. Organisational human factors, as described by Charalambous et al. [20], represent the combinations of organisational and individual characteristics that influence employee behaviour at work. These factors shape how individuals perform tasks and interact with people.

Adoption Barriers: These are the obstacles that hinder the complete adoption, implementation or use of innovations or technology within an organisation. Organisations need to recognise not only the enablers but also the barriers that may hinder the adoption process and overcome them to preserve organisational competitiveness.

3.3 Research Questions

The literature review reveals several gaps in the literature on cobots adoption in manufacturing SMEs. Therefore, the main research question is outlined below:

How to develop a holistic cobot adoption model for Australian manufacturing SMEs?

As previously discussed, it is clear that a holistic model for cobot adoption by manufacturing SMEs does not currently exist in the Australian context. Although several efforts to develop such models have been conducted in various countries, as shown in Table 2.13, Chapter 2, the number and type of factors in these frameworks differ across studies. This indicates that, although the classification among dimensions remains relatively unchanged, various factors may be incorporated depending on the specific setting. This work investigates the determinants of cobot adoption in Australian manufacturing SMEs. Accordingly, the main research question is structured around five sub-questions:

Research Sub-Question 1: *What technological factors influence Australian manufacturing SMEs' intention to adopt collaborative robots?*

Research Sub-Question 2: *What organisational factors influence Australian manufacturing SMEs' intention to adopt collaborative robots?*

Research Sub-Question 3: *What environmental factors influence Australian manufacturing SMEs' intention to adopt collaborative robots?*

Research Sub-Question 4: *What human factors influence Australian manufacturing SMEs' intention to adopt collaborative robots?*

Research Sub-Question 5: In addition to enabling factors for the adoption of collaborative robots in manufacturing SMEs, several barriers slow down or prevent their adoption. The following sub-question is identified:

What are the adoption barriers that Australian manufacturing SMEs face in adopting collaborative robots?

3.4 Research Objectives

Based on the aforementioned research question and subquestions, the main aim of this research is as follows:

To develop an appropriate holistic collaborative robot adoption framework in Australian manufacturing SMEs.

The research aim can be achieved by developing and validating a merged model for the adoption of cobots in Australian manufacturing SMEs. Although existing adoption frameworks or models are provided in the literature, this thesis is based on the main view that adoption factors will differ depending on the context. Phase 1 of the thesis adopts qualitative research to determine the relevant enabling factors and adoption barriers in the intended settings. Then, Phase 2 employs quantitative research, using a survey targeting more than 200 respondents to test hypotheses and confirm whether the relationships are supported or rejected. To achieve this aim, it is essential to explore the factors that influence cobot adoption in Australian manufacturing SMEs, whether positive or negative, through different dimensions. Therefore, the research objectives are described below:

Research Objective 1: *To develop an initial comprehensive model for collaborative robot adoption in Australian manufacturing SMEs based on a related empirical literature review and theoretical foundation.*

To achieve this objective, relevant theories on technology adoption are reviewed to identify and select the most appropriate factors that have been empirically confirmed in research to influence the adoption of cobot technology and other manufacturing technologies, particularly in light of the limited literature on cobot technology adoption theories in the manufacturing context. The solution to this objective is given in Chapter 2, Chapter 4 and Chapter 5.

Research Objective 2: *To refine the adoption model by incorporating key factors to align with the context of Australian manufacturing SMEs.*

To achieve this objective, in phase 1, qualitative insights are gathered through interviews conducted with decision-makers from Australian manufacturing SMEs. After completing the analysis, the factors perceived as non-influential by the interviewees will be excluded from the model. Additionally, several new factors which may not have been studied in the earlier works but are relevant to the context of Australian manufacturing SMEs may be included. Then, these modifications will refine the conceptual model. The solution to this objective is given in Chapter 6.

Research Objective 3: *To empirically test and validate the relationships between the enabling factors and barriers included in the refined model for adopting collaborative robots with a larger representative sample of manufacturing SMEs in Australia.*

To achieve this objective, Phase 2 involves applying quantitative research using a questionnaire. After completing the analysis, the model will be assessed for its suitability in exploring the factors, and the influencing factors in the specified setting will be identified. The solution to this objective is given in Chapter 7.

Research Objective 4: *To provide new theoretical and practical insights based on the research outcomes related to collaborative robot adoption and applications in manufacturing SMEs.*

To achieve this objective, this work positions its findings within the available studies on cobot technology adoption in manufacturing. The findings will be compared with the studies reviewed in Chapter 2 and the proposed hypotheses. Special emphasis will be on inconsistencies between the results and the expectations. The study will also outline the theoretical and practical contributions. In Chapter 8 and Chapter 9, the solution to this objective is given.

3.5 Conclusion

In Chapter 3, the study problem was introduced, and the key terms used were defined. The thesis objectives and questions were outlined, drawing on the identified gaps and approaches in the review.

In the following chapter, based on related theories and approaches from the literature, the study presents an overview of the solutions and the methods proposed to tackle the thesis questions and fulfil the intended objectives.

Chapter 4

Methodology and Solution Overview

4.1 Overview

Chapter 4 offers the proposed solution to the study questions and identifies the general methods for its application. The fundamental terms applied across this chapter are defined in section 4.2. Section 4.3 offers a summary of the problem-solving approach, the choice of theoretical frameworks that underpin the collaborative robot (cobot) technology model in Australian manufacturing SMEs, and the proposed solutions to the research subquestions (RQ1-RQ5). A mixed-methods design and its justification are detailed in the research methodology in section 4.4. Section 4.5 offers phase 1 (qualitative), which includes the model and provides an initial analysis by several industry experts. Section 4.6 presents phase 2 (quantitative), which involves the quantitative testing and evaluation of the model, conducted using a large-scale sample of senior, middle management, and technology specialists from Australian manufacturing SMEs, as outlined in section 4.6. Ethical concerns are outlined in section 4.7. Sections of Chapter 4 have been published as follows:

- M. Haddas and F.K. Hussain, "Technology Factors Affecting Australian Manufacturing SMEs Adoption of Collaborative Robot Technology: A Qualitative Interview Study,". In *Proceedings of the 43rd International Business Information Management Association Conference (IBIMA)*, Madrid, Spain, June 2024.
- M. Haddas and F.K. Hussain, "Human Factors Influencing Australian Manufacturing SMEs' Adoption of Collaborative Robots: A Qualitative Study. In *Advanced Information Networking and Applications: Proceedings of the 39th International Conference on Advanced Information Networking and Applications (AINA-2025)*, vol. 7, Cham, Switzerland: Springer, 2025, pp. 154-164.

4.2 Main Definitions

In this chapter, the following terms are frequently used and defined for clarity:

Theory: This is a set of propositions, definitions and concepts interrelated with systematically interpreting phenomena. The development of theories relies on reasoning and empirical evidence to ensure that these theories are verifiable and testable. The selection of a theory in any research is essential to make sense of and contextualise the research results, thus improving the results' validity and reliability and contributing to knowledge [65].

Research Framework: This is the blueprint or conceptual structure that directs the entire study process. A research framework encompasses the key theories, variables, study hypotheses, research questions, data analysis procedures, and methods that shape the research design and implementation. It serves as a roadmap for conducting the study, ensuring that it is well-organised, coherent, and consistent [66].

Research Design: This is the overall strategy or structure for answering a research question by collecting and analysing data. It presents the methods and techniques to be employed in collecting and analysing research, and offers a model for applying the work credibly and thoroughly. As a relevant part of the research process, it ensures the work is properly implemented, well-designed and that the outcomes are valid and reliable [6].

Research Methodology: This refers to the systematic plan and specific techniques used to undertake research. It involves data analysis and collection, research design and the interpretation of outcomes. It provides a model for carrying out an organised and systematic investigation and ensures that the research is credible and rigorous [52].

Qualitative Research: This form of research aims to comprehend human behaviour by exploring individuals' perceptions and subjective experiences by collecting data through methods that are considered open-ended and in-depth, such as research observations, ethnography, focus groups, and interviews. It seeks to offer a detailed, precise, and rich comprehension of the respondents' insights, rather than generating numerical data or testing hypotheses [67].

Quantitative Research: This form of research aims to understand phenomena by describing them using statistical and numerical data. It involves collecting quantitative data and analysing it using structured and standardised methods, such as observations, surveys or experiments. It seeks to test hypotheses, identify patterns and relationships, and generalise findings. It often employs statistical techniques to draw inferences from the analysed data [6]. Quantitative research is often utilised in various fields, such as psychology, public health, and sociology, to offer an understanding of the research subject.

Mixed Research: This form of research integrates quantitative and qualitative methods; mixed research enables a subject to be studied and analysed from different views. This approach, therefore, offers a broader understanding of the phenomenon. In this type of research, qualitative methods are employed to achieve a thorough understanding of a specific issue and quantitative methods are applied to examine particular hypotheses and offer generalisations. This research design is relevant to situations where the study question is complex and needs a rich and detailed understanding of perspectives and expertise, as well as allowing comparisons and quantifiable inferences to be made from the results [7].

4.3 Overview of the Solution

4.3.1 Approach to the Proposed Solution

To develop the overall solution to the research question, the design science approach [68] is followed in this thesis. Figure 4.1 shows the six-phase framework along with the corresponding chapters of the thesis.

- **Phase 1: Problem identification and solution value**

  The relevant academic literature reviewed in this phase highlighted the limitations and knowledge gaps in cobot adoption in the manufacturing SMEs industry were analysed to identify the research problem to be addressed (Chapter 2). Then, the sub-questions and primary research question were designed based on the review (Chapter 3). The proposed solution value was provided by emphasising the significance of new technologies and innovations for manufacturing

SMEs (Chapter 1).

- **Phase 2: Define the solution objectives**
  After formulating the key sub-questions and primary research question, the primary objective of the thesis was outlined. The solution seeks to offer a suitable model for cobots adoption by Australian manufacturing SMEs. In Chapter 3, several relevant objectives were identified to ensure a holistic approach to the study phenomenon. To fulfil these objectives, various resources were used: existing empirical and theoretical research on technology adoption, opinions from industry experts, and data collected through a quantitative questionnaire to establish the model's role element.

- **Phase 3: Development**
  The first aspect presented in Phase 3 involves developing an original framework for the adoption of cobots by Australian manufacturing SMEs. This framework, referred to as the Holistic Collaborative Robot Adoption Model (HCRAM), is created based on the following: 1) a review and assessment of existing frameworks and theories; 2) the combination of the most appropriate; and 3) the determination of the main aspects of the model drawn from empirical works. This process is carefully documented in the subsequent sections of Chapter 4. The proposed HCRAM is described, including the relationships among the framework's elements (Chapter 5).

- **Phase 4: Demonstration**
  The main significance of this phase is providing a refined HCRAM for cobot technology adoption by Australian manufacturing SMEs, as detailed in Chapter 6. To accomplish this, the HCRAM conceptual model was evaluated by several industry experts. These experts offered insights into the framework and its proposed elements, and also recommended further components they deemed suitable for the Australian manufacturing SME context. This constitutes Phase 1 of the thesis and yields a key result: a refined HCRAM.

- **Phase 5: Evaluation**

In the evaluation phase, a key result is the provision of empirical evidence that validates the refined HCRAM model in examining and evaluating cobot technology adoption in Australian manufacturing SMEs, and in assessing the effectiveness of its elements, as detailed in Chapter 7. To achieve this, the study uses a large sample of industry experts, including managerial and technology specialists from Australian manufacturing SMEs, to test the refined HCRAM. This constitutes Phase 2 of the study

- **Phase 6: Communication**

  In this phase, the study findings are summarised, analysed, and communicated to the target audiences. Chapters 8 and 9 present a discussion of the conclusions and study outcomes. Selected findings have been presented at conferences, and further publications are anticipated following the completion of this thesis.

  The solution approach for selecting the adoption model, as outlined earlier, begins with identifying the most appropriate frameworks to serve as the foundation.

4.3.2 Theoretical Framework Selection

With the integration of telecommunications, smartphones, tablets and the internet, coupled with rapid technological development, the shift driven by emerging technologies has become increasingly evident in recent decades. Thus, there is a growing need for the adoption of frameworks and theories that can help explain why and how emerging technologies are adopted, and which factors are important in the adoption process [69]. Several adoption frameworks were considered when selecting the most suitable as the foundation for this study.

The process of technology adoption is generally divided into two levels, of which the first pertains to the individual level, several established theoretical frameworks used in this level, including the Theory of Reasoned Action (TRA) [70], the unified theory of acceptance and use of technology (UTAUT) [55], the theory of planned behaviour (TPB) [71], and technology acceptance model (TAM) [72], These theories relevant

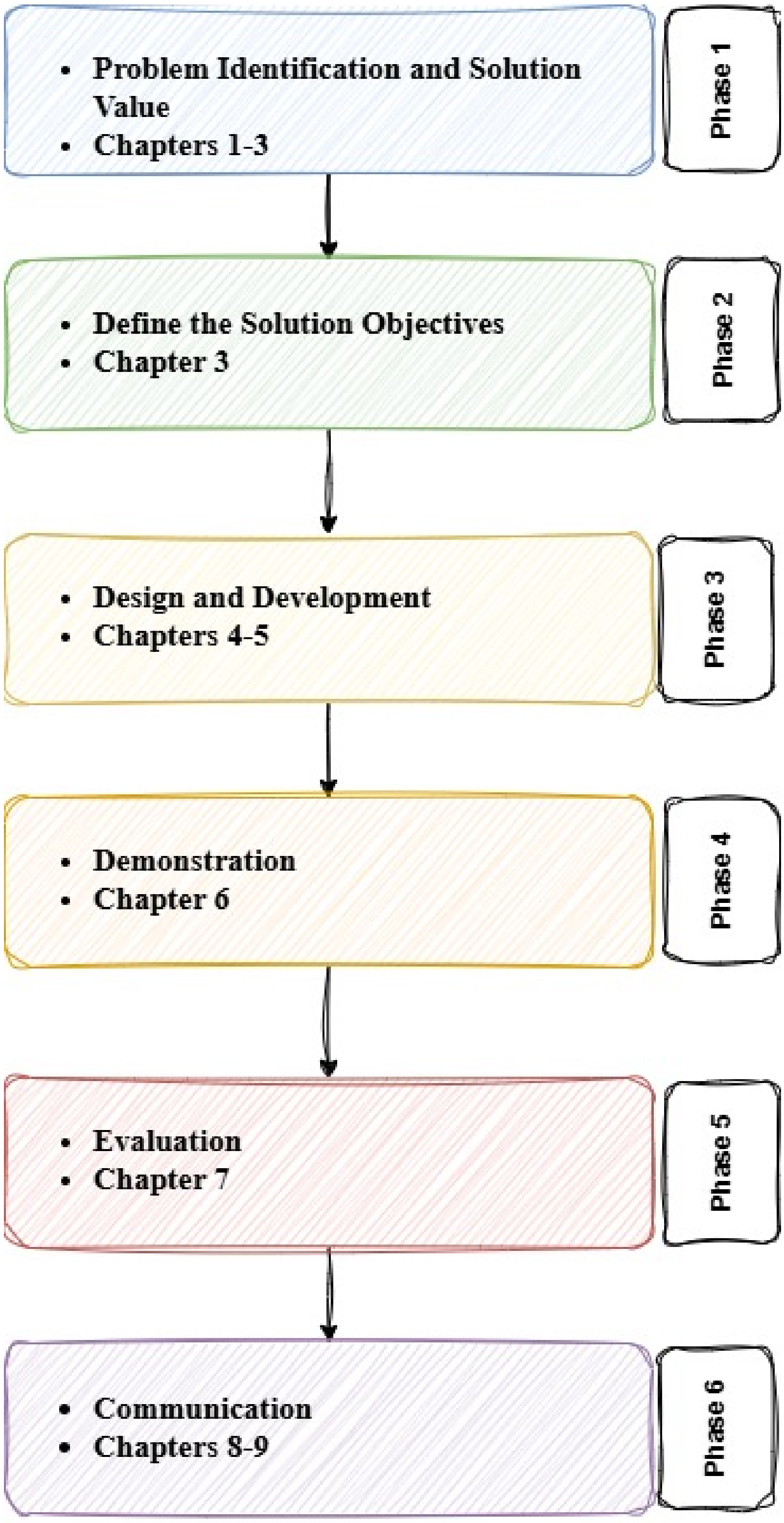

Figure 4.1 : Approach to the Problem Solution

to individual user acceptance and intention, but overlook organisational context. Thus, they do not fall within the scope of the thesis.

The second level is the organisational level, which is concerned with the current work, i.e., studying how manufacturing SMEs adopt cobot technology. At the organisational level, several technology adoption frameworks and theories from the information system (IS) field are relevant, such as the TOE framework [4], the DOI theory [63], and institutional theory (IT) [73]. The following subsection provides a review of these theories at the organisational level. Finally, the selection of the TOE and DOI framework is justified as the theoretical basis for this work.

Institutional Theory

In organisational theory, the institutional paradigm explains organisational changes through processes of organisational legitimacy [74]. In the larger social environment, institutional sources of legitimacy are present in common actions, traits, features, and structures that integrate to create a sense of reality through their presence. These sources exert pressure on all entities in the environment to emulate these main attributes. According to [73], the institutional environment of an organisation is shaped by three types of isomorphic (i.e., similar) pressures: coercive (i.e., related to legitimacy concerns and political influence), normative (i.e., related to professionalisation) and mimetic (i.e., standard responses to uncertainty). Organisations perceive these pressures as forms of direct competition and bandwagon influence, which manifest as shared patterns among trading partners. Organisations that fail to align with these patterns risk falling behind [75].

As discussed in Chapter 2, one study conducted in large manufacturing firms [24] and another in manufacturing SMEs [23], both incorporated institutional theory with the DOI and TOE frameworks to examine cobot adoption in their respective contexts. However, these studies did not provide details of the mechanisms of institutional isomorphism; instead, they focused on theoretical integration with other theories. Both studies utilised environmental factors such as external pressure and regulations on IT adoption, which are available as part of the TOE framework. Furthermore, institutional theory is focused on legitimacy, which is less appropriate for the study objectives. This theory, therefore, was not selected as a theoretical basis for this study.

Diffusion of Innovation Theory

This theory aims to explore why and how innovations and ideas spread across cultures [76]. In various disciplines, the DOI theory [63] is regarded as an important adoption theory, particularly in organisational adoption studies [69],[77]. The DOI theory further aims to identify the influential factors that drive innovation in society [3], and define why one new technology or innovation succeeds while others do not. Users' perceptions of innovation and technology characteristics are generally considered the basis of this theory.

According to Rogers' theory of innovation [3], four main elements are perceived as important for adoption: a social structure, the innovation itself, a time frame, and communication channels. The element of innovation refers to a new process, product, idea, technology, or service as perceived by individuals or any other unit of adoption [3]. According to DOI theory, knowledge about innovation differs between organisations and individuals, with innovation signifying something new to the intended recipients. Accordingly, for this thesis, cobot applications (i.e., the innovation) represent a novel approach in manufacturing SMEs, particularly in Australia. The communication channel element facilitates the transmission of innovation from one firm or individual to another [3]. This refers to the tools or channels used by individuals to share knowledge and interact with others, thereby increasing awareness of the innovation. Two types of communication channels [3] are identified: mass media, which disseminate information to the public, and internal channels, which influence people's adoption decisions. As noted by [78], both learning processes and effective communication can support the adoption of innovation. Then, appropriate communication strategies are required to persuade and educate target audiences about the value of the technology. In the DOI theory, time is a critical element, which enables the process of diffusion of innovation through various stages [3]. This element comprises three dimensions. Regrading the innovation of decision process, the first dimension includes five phases: knowledge, persuasion, decision, implementation, and confirmation. The second dimension categorises the adopters in the same social system as either late or early adopters. The third dimension refers to the innovation pace, which is commonly assessed through the individuals or firms that adopt the innovation [3]. The details of these dimensions are discussed below. The social system element represents the final component relevant to technology adoption and is defined as *" a set of interrelated units that are engaged in joint problem solving to accomplish a common goal"* [3]. Within the social system, the diffusion of an innovation is influenced by several systemic features, such as innovation outcomes, innovation decision types, opinion leaders, social norms and structure. Regarding social structure, Rogers [3] describes it as *" the patterned arrangements of the units in a system"*.

The decision-making process in DOI theory involves five stages, as previously outlined in Figure 4.2. In the first stage, *knowledge* of the technology is relevant for potential adopters to understand the technology and how it functions. This is followed by the *persuasion* stage, which acts as a decision borderline, where the assessment of information becomes more credible because it is usually influenced by current technology users and peer recommendations. The third stage involves the *decision* to disregard or adopt the new technology. Notably, at any stage of the process, the technology can be rejected, even if a positive decision is made, thus halting progression to subsequent stages. In cases of adoption, the *implementation* stage entails the practical applications of the technology. During this stage, the technology is also evaluated regarding complexity, benefits and usability. In the final stage, *confirmation*, adoption is reinforced. As shown above, the early stages of the innovation-decision process model are essential in determining the subsequent stages of adoption. The *knowledge* stage acknowledges that the units of decision making differ depending on whether the adopters are individuals or organisations [3]. The *persuasion* stage involves five key attributes of innovation that significantly influence the adoption decision. In adoption research, these attributes have been regarded as dominant technology factors [77]. Each attribute affects how the innovation, idea, or product is perceived and adopted. Table 4.1 provides a concise overview of these five attributes. According to [3], adopters are categorised into

[Production note: This figure is not included in this digital copy due to copyright restrictions.]

Figure 4.2 : Phases of the Innovation-Decision Process [3]

Table 4.1 : The Five Innovation Attributes

Attribute	**Definition**	**Source**
Relative advantage	"the degree to which an innovation is perceived as superior to its predecessor"	[3]
Compatibility	"the degree to which an innovation is perceived as consistent with existing values, past experiences, and needs of potential adopters"	[3]
Trialability	"the degree to which an innovation may be experimented with on a limited basis"	[3]
Observability	"the degree to which the results of an innovation are visible to others"	[3]
Complexity	"the degree to which an innovation is perceived as relatively difficult to understand and use"	[3]

different groups based on their behaviour toward innovation adoption, as illustrated in Figure 4.3. *Innovators* are the first group to adopt innovation, comprising a small proportion of adopters (2.5%). Generally, they have knowledge and awareness about innovations and are extremely interested in being among the earliest to use them [3]. Further, they typically have access to financial resources that mitigate the risks associated with potentially unprofitable innovations and the high level of uncertainty around innovation adoption. *Early adopters* are the second group, accounting for approximately (13.5%) of adopters. These individuals possess the highest level of opinion leadership and are particularly Change-oriented. Overall, they consider it relevant in the persuasion and knowledge phase of the innovation-decision-making model. The *early majority* is the third group, representing (34%) of adopters. These individuals are generally cautious and make adoption decisions only after assessing the reputation of the innovation. They act as a connection between early and late adopters. The early majority takes more time to make adoption decisions than innovators and early adopters. The *late majority*, another 34% of adopters, tend to be sceptical or innovations and the benefits they may offer. According to [3], they adopt technologies only once they have become thoroughly tested as they often have relatively limited resources. The late majority usually adopt innovation due to economic necessity and peer pressure [3]. *Laggards* are the last group of adopters, accounting for 16% of the population. These individuals are often doubtful of change agents and innovation, and therefore, they may tend to have a low level of awareness and knowledge about innovations. According to Rogers [3], the number of innovation adopters across the five groups is generally distributed over time. Each group possesses different attributes that influence its adoption behaviour. As illustrated in Figure 4.3, the two largest groups are the early majority and the late majority.

In the field of technology adoption, the DOI is one of the popular and widely applied in diverse research areas [79]. It has also been tested within a range of contexts, such as information systems, healthcare, and education[3],[80]. Earlier literature has validated the five technology attributes of the DOI that influence the process of any technology adoption [69]. Several current examples that investigate the adoption of emerging technologies across different disciplines and industries include IoT

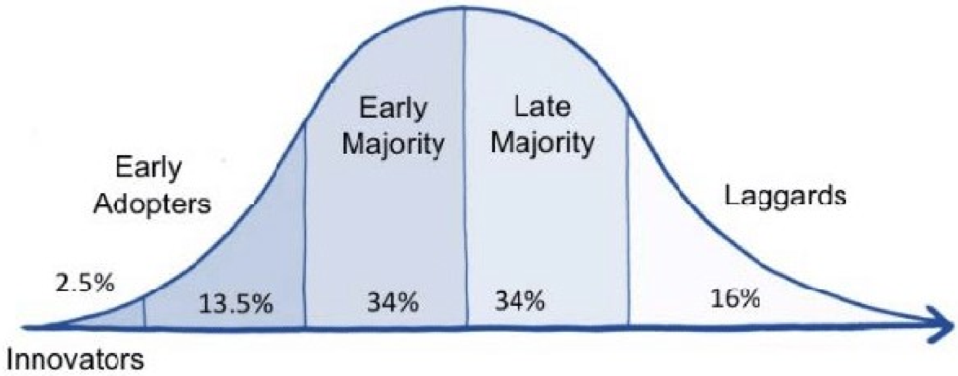

Figure 4.3 : Categories of Innovation Adopters over Time [3]

adoption in healthcare [81], mobile wallet adoption in the financial sector [82], and autonomous vehicle adoption in the transportation industry [83], among others.

As discussed in Chapter 2, very few studies have applied the DOI theory with other frameworks to study cobots adoption in the manufacturing field. The five technological attributes of the DOI theory have been explore in several contexts: in large manufacturing companies in Portugal and France (all five attributes) [24], in manufacturing SMEs in Portugal (two attributes) [23], and manufacturing SMEs in Guangdong Province, China (all five attributes) [54]. Although these studies demonstrate the applicability of DOI theory in examining cobot adoption (an emerging technology), they still represent a nascent trend that requires further investigation of all five DOI technology attributes, particularly within the context of manufacturing SMEs in Australia. Accordingly, these findings reinforce the appropriateness of DOI a theoretical basis for this thesis.

Despite its contributions, the DOI theory has several limitations. A significant limitation of DOI is that it conceptualises diffusion as a discrete process that occurs in socially homogeneous and static environments [84]. According to [85], in many cases, complex systems (i.e. technological systems) are explained and perceived differently depending on the specific context of place and time. As a result, technology adoption may be influenced by economic realities, as well as socio-political dynamics, infrastructural constraints, and local traditions. This is particularly applicable to organisations that are more influenced by environmental structures than by individual users. Thus, several researchers have suggested that technology adoption and diffusion should be driven over time by organisational and environmental forces [86],[87]. The DOI concentrates on the attributes of the technology itself, with less attention to these influences. A further limitation of the DOI theory, as a generalised theory, is that it identifies the process of innovation diffusion as occurring over a relatively short timeframe within fixed stages and mostly excludes the influence of prior processes of decision making [84]. This means that the DOI regards technological characteristics and organisations as linear or stable over time and may exclude feedback from the system [85]. Instead, this may not be the case, and the role of organisational evolution, historical, and process aspects should be reconsidered [88]. Overall, the DOI theory focuses on the role of technological features compared to environmental and intra-organisational contexts. It is also criticised due to the absence of feedback and its stable nature. To overcome these shortcomings, this thesis combines the TOE framework with DOI theory [4], seeking to establish and design both a thorough and flexible framework based on a solid theoretical basis.

Technology-Organisation-Environment Framework

At the organisational level, the TOE framework is also the most prominent model, developed by [4] to analyse the implementation and adoption of new technologies [89]. Regarding the adoption process, this framework consists of three key contexts: the technology context, the organisation, and the environment, as shown in Figure 4.4.

Technology Context: This context is applied to an organisation to explain applicable external and internal technologies [90]. Drawing on the TOE framework, two forms of technology adoption are linked to the broader process of new technologies adoption: first, the technologies currently implemented in organisations, which determine the limits and scope of potential developments, and second, technologies present in the marketplace but not currently in use, highlighted what could potentially be achieved [4]. Further, [4] defines three types of external technologies based

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Figure 4.4 : TOE framework [4]

on the nature of change they bring to the existing technology: discontinuous, incremental or synthetic. Discontinuous change technologies are completely different from those available in the organisation [89]; incremental change technologies enhance existing systems by adding new features or characteristics and pose the least risk to organisations. According to [89], these technologies exert a gradual influence across the organisation. For example, the adoption of LCD monitors in personal computers did not require immediate operational changes; synthetic different technologies integrated available technologies in an innovative method and present a manageable risk to organisations. According to [4], the impact of this type of technology change occurs over time. A cobot is considered one of these as it introduces a new form of hybrid work environment in manufacturing that did not exist before, which integrates robotics and human capabilities. Accordingly, organisations should pay close attention to the innovations that need to be introduced and analyse the expected changes resulting from the adopted innovation. The technology dimension and its characteristics were originally incorporated in the TOE framework as the key factors influencing the adoption of innovation [4]. However, further factors have also been effectively incorporated and examined. The five technology attributes of the DOI theory are typically used under the technology context in the TOE framework [24],[54]. Several common factors in the technology context are perceived costs and technology readiness [56],[58],[91],[92].

Organisational Context: This context refers to the internal attributes and resources of a firm that affect the process of innovation adoption [89]. According to [4], three mechanisms contribute to this influence. First, internal groups and individuals who support innovation, such as technology gatekeepers, opinion leaders, and innovation champions. Second, new technologies or services can be supported by multi-disciplinary teams that have connected with partners and organisational departments. Third, structures of organisations that are more directive, support innovation and are decentralised. Additionally, communication ways may either impede or support technology [4]. Within the TOE framework, the leader has a pivotal role by supporting and connecting the new technology consistently with the strategic vision and mission of the organisation, or by providing a clear justification for the reason the technology may not be compatible with the organisation's overall strategic orientation. Within the original TOE, the effects of the two other factors, slack and organisational size, remain uncertain regarding technology adoption. According to [89], larger firms have traditionally been connected with being more suitable for adopting innovation; however, subsequent research presents more mixed and inconsistent results [89]. It is often argued that organisational size may lack the precision required to allocate targeted sources needed to support adoption [89]. Similarly, organisational slack has been acknowledged as promoting innovation in several traditional organisational studies [93], and even within the DOI theory [4]; however, the existence of slack does not necessarily reflect adoption. Given these two factors serve as uncertainty, subsequent studies have added further factors such as the readiness of organisations and IT infrastructure [24],[54],[91],[94].

Environmental Context: This context represents the external ecosystem surrounding the organisation, however it is often beyond its direct control. Intense competition often prompts the adoption of novel technologies to gain a competitive advantage. Such competition is one of the environmental mechanisms that affect innovation adoption [4]. Similarly, dominant partner organisations encourage firms to adopt innovation to enhance cross-organisational operations and maintain business relationships. Additionally, adoption occurs more quickly in environments with an appropriate technology infrastructure and a sufficient supply of technologies [89]. Finally, government regulations can constrain innovation by imposing restrictions or high implementation costs on the technology to be adopted [89].

The environmental context, like the technology and organisational contexts, has been modified in different studies to include or exclude specific variables. Several studies, for example, identify government support as one of the most dynamic and frequently modified element in the environmental context [54],[56],[57],[91],[94].

As a result, within the TOE framework, the three contexts within the organisational level encompass influential dimensions that facilitate the adoption of decision-making practices. These dimensions include factors that may either support or hinder the adoption of technology by organisations. Notably, the TOE framework does not impose limitations on the types of factors considered within each dimension, offering researchers a valuable opportunity to explore a broader range of environmental factors. This flexibility aligns with the objectives of this thesis, as new environmental elements are expected to emerge.

At the organisational level, the TOE framework is widely recognised as a framework for analysing innovation adoption and is often compared with other theories, such as DOI theory [24],[56],[59]. This framework allows researchers to add or remove factors based on contextual needs without requiring modifications to its fundamental structure [95]. According to [89], TOE is valued for its flexibility in integrating with similar theories, such as the DOI theory, enabling a unified approach to the adoption process rather than presenting competing perspectives. TOE is also recognised as a suitable framework for research on emerging technology adoption [24],[90].

Within the manufacturing field, the TOE framework has been applied to explore the process of innovation adoption, particularly in areas such as big data analytics [96], 3D printing [97], and AI-empowered industrial robots [94], among others. Despite this, as discussed in Chapter 2, very few studies have used TOE to study the adoption of cobots in manufacturing SMEs [23],[54]. Hence, it is essential to empirically validate the framework and evaluate its application in various manufacturing settings, including the current study.

4.3.3 The Enhanced Framework (DOI-TOE): Selection and Justification

Many studies have advocated frameworks that integrate more than one theoretical view to understand new technologies [90],[98]. A comprehensive research context is essential to understand organisational decisions surrounding technology adoption, particularly when it relates to the nature of the technology itself [99]. The thesis relies on two theoretical underpinnings: the TOE framework and the DOI theory. The selection of the DOI and TOE frameworks is justified for several reasons. First, this combined framework facilitates the adoption of innovative technology in manufacturing SMEs at the organisational level. As previously mentioned, adoption theories such as UTAUT and TAM primarily focus on individual-level adoption. Indeed, research on cobot adoption using these theories highlights the significance of individual factors, for example, perceived usefulness, facilitating conditions, prior performance experience [21],[40]. Although these factors are critical in understanding the acceptance of cobots, they clarify little regarding the organisational and intra-organisational dynamics that influence how such technologies are introduced to support operational and strategic objectives and how the diffusion process occurs. In particular, cobot adoption in the SME context is primarily an organisational decision that involves different stakeholders and strategic considerations; hence, individual-level theories are regarded as being outside the scope of the thesis. Some researchers propose a socio-technical system (STS) theory to study cobots in a manufacturing setting, as discussed in 2 . For example, one study utilised the STS approach, along with various factors [36], and another study employed a conceptual model that combined STS with the UTAUT model [40]. According to [100],[101], the STS approach is a broad theoretical framework that includes two components: social and technological subsystems. This framework is relevant to designing the interactions between robots and humans. Although this approach is helpful in a workplace environment that has already implemented innovations (i.e., after adoption), this means it does not study whether the adoption phase occurs, making it inappropriate for studying adoption decisions. Further, the STS perspective often overlooks important aspects of innovation diffusion and the internal and external determinants that are necessary for a comprehensive understanding, which is important in the SME case in a competitive market.

This study also clarifies that institutional theory was used in two similar studies [23],[24], combining it with DOI and TOE at the organisational level. However, institutional theory is deemed less relevant to this research, as its key constructs are already encompassed within the TOE framework, making institutional theory redundant in the proposed theoretical structure.

In summary, the selection of the TOE framework and DOI in the current work at the organisational level, as discussed, is based on their alignment with the thesis context and objectives. This choice is consistent with prior works in the adoption field at the organisational level, adapted from the TOE framework and DOI [90],[102]. Together, such an integrated framework offers a solid research foundation for exploring innovative adoption of across the manufacturing SMEs industry. The need for this integration arises from the inability of either framework to examine all possible factors influencing technology adoption in organisations thoroughly. While DOI emphasises the technological attributes of innovations, it is less effective in explaining the impact of organisational and environmental contexts. Conversely, the TOE framework includes technology dimensions but lacks the ability to specify and validate the technology attributes essential for the adoption process. As recommended also by [90], the TOE and DOI theory meaningfully complement each other.

This integrated framework has been extensively applied to exploring the effecting adoption determinants of different manufacturing technologies, for example, cloud computing (e.g. [56]) and cloud-based ERP systems (e.g. [92]). More recently, the adoption of cobots in manufacturing SMEs has received attention in only a small number of empirical investigations that employ this enhanced framework, as discussed in chapter 2. One such work was employed in Guangdong Province, China [54]. Another study by [23] applied an integrated framework combining DOI, TOE and institutional theory to examine innovation adoption in Portuguese manufacturing SMEs. Based on these clarifications, this study, therefore, contends that the TOE and DOI can be extended to study cobots adoption, an emerging innovation in Australian manufacturing SMEs at the organisational level. Due to the flexibility of the TOE, the thesis suggests integrating new contexts depending on the research objectives. Notably, two new contexts are suggested: the human context, viewed through the decision makers' perspectives, and the adoption barriers. Consequently, the conceptual framework in this thesis contributes by including five main contexts: technology, organisational, environmental, human, and adoption barriers, to facilitate an extensive comprehension of the diffusion of innovation adoption in Australian manufacturing SMEs.

4.3.4 Overview of Solutions to Research Sub-questions

The following procedures involved identifying the specific adoption factors for cobot in Australian manufacturing SMEs, after selecting a general theoretical framework as the basis for the proposed model. An empirical literature review is conducted, viewed in light of the DOI and TOE theoretical perspectives, exploring and discussing the related factors linked to cobots. To provide a solution to each sub-question, a common approach used is shown in Figure 4.5.

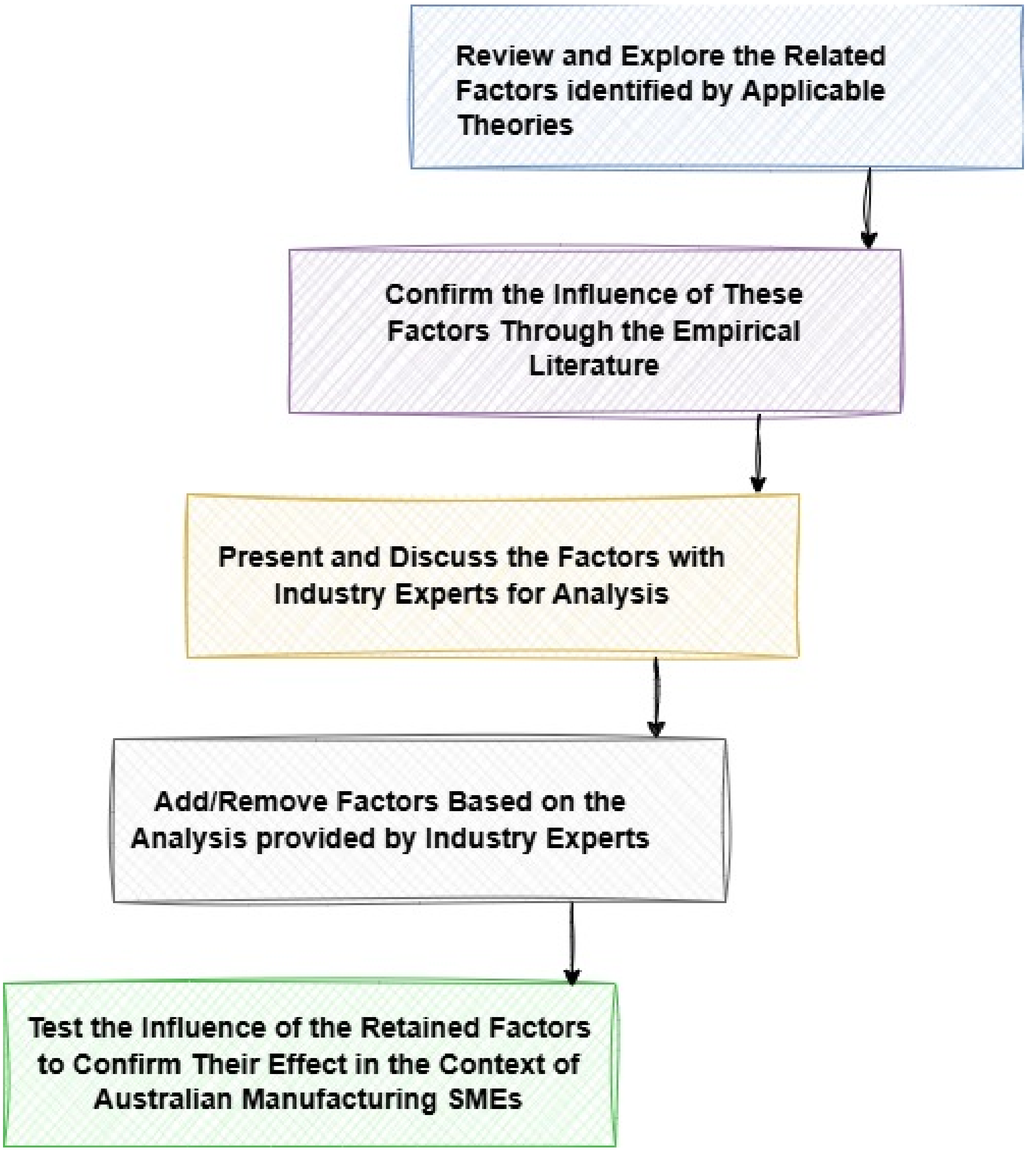

Figure 4.5 : The Solution Approach to Each Research Sub-question

Overview of Solutions to Research Sub-Questions RQ1, RQ2 and RQ3

The purpose of RQ1, RQ2, and RQ3 is to explore the technological, organisational and environmental (external) factors influencing the adoption of cobots in Australian manufacturing SMEs.Given the ongoing evolution of new technology like cobot, there has been a few empirical works that apply DOI and TOE frameworks to the adoption of cobots in manufacturing SMEs. This research expands its scope to include other relevant manufacturing technologies, such as AI-powered robots, Industrial Internet of Things (IIoT), etc, that have been examined through integrated applications of the DOI and TOE frameworks in the manufacturing context. Although these technologies differ in some aspects from cobots, they have similar adoption or acceptance challenges. Thus, a broad range of empirical literature on the adoption of cobots and other manufacturing technologies has examined various integrative approaches combining factors from the DOI and TOE frameworks. These studies identified the influence environmental, organisational, and technological factors through these theoretical lenses, as outlined in Tables 4.2–4.4.

Table 4.2 : Technological (DOI) Factors Influencing Adoption of Digital Technologies

Innovation studied	**Source**	**DOI Factors**
Cloud Computing	[56]	Relative advantage, Complexity, Compatibility
Big Data Analytics	[96]	Complexity, Compatibility
B2B e-commerce	[57]	Relative advantage, Compatibility, Complexity
B2B e-Commerce	[91]	Perceived relative advantage
3D printing	[97]	Relative advantage
Digital technologies of smart manufacturing	[58]	Perceived compatibility
Industry 4.0	[60]	Relative advantage, Complexity, Compatibility
IIoT	[59]	Relative advantage, Compatibility
Cloud-based ERP	[92]	Complexity, Compatibility, Relative advantage
Big Data	[103]	Relative advantage
Collaborative robots	[24]	Relative advantage, Compatibility, Complexity, Trialability, Observability
AI-powered robots	[94]	Perceived compatibility
AI technologies	[104]	Complexity
Collaborative robots	[54]	Relative advantage, Compatibility, Complexity, Observability, Trialability
Leagile manufacturing system	[105]	Relative advantage, Compatibility, Complexity
Generative Artificial Intelligence (GenAI)	[61]	Relative advantage, Compatibility, Complexity
Collaborative robots	[23]	Relative advantage, Compatibility

Table 4.3 : Organisational and Environmental Factors Influencing Adoption of Digital Technologies

Innovation studied	Source	Organisational Factors	Environmental Factors
Cloud Computing	[56]	Top management support, Firm size	Regulatory support, Competitive pressure
Big Data Analytics	[96]	Top management support, Organisation data environment, Perceived costs	External pressure, Industry type
B2B e-commerce	[57]	Top management support, Firm size	Competitive pressure, Business partners' pressure
B2B e-Commerce	[91]	Top management support, IT infrastructure and capabilities	Competitive pressure, Trading partner pressure, Government support, Legal infrastructure
3D printing	[97]	Organisational readiness, Top management support, managerial obstacles	Competitive pressure, Expectations of market trends, Trading partner, Government policy

Continued on next page

Table 4.3 (continued)

Innovation studied	Source	Organisational Factors	Environmental Factors
Digital technologies of smart manufacturing	[58]	Information and digital technology knowledge, Information processing, Strategic roadmapping for manufacturing digitalisation	Environmental imposition, Competitive pressure
Industry 4.0	[60]	Top management support and championship, Satisfaction with the existing system, Organisational structure	Market uncertainty, Industry cluster
IIoT	[59]	Top management support, Organisational readiness	Competitive pressure, Vendor support
Cloud-based ERP	[92]	Top management support, Firm size, Cloud knowledge	Competitive pressure, Regulatory support
Big Data	[103]	Management support, Firm size	Competitive pressure, Trading partner readiness, Regulatory environment

Continued on next page

Table 4.3 (continued)

Innovation studied	Source	Organisational Factors	Environmental Factors
Collaborative robots	[24]	Top management support, Receptiveness, Readiness	Competitive pressure, Business partner, Government directives, Regulatory environment, Technology infrastructure, Financing agencies
AI-powered robots	[94]	IT Infrastructure	External pressure, Vendor support
AI technologies	[104]	Company size, Competitive factor, R and D intensity, Digital skills	Industrial sector, Country
Collaborative robots	[54]	Top management support, Organisational readiness	Vendor support, Competitive pressure, Government support
Leagile manufacturing system	[105]	Management commitment, Resistance to change, Organisation capacity, Firm size	Competitive pressure, Customer link, Supplier involvement, Environmental uncertainty

Continued on next page

Table 4.3 (continued)

Innovation studied	Source	Organisational Factors	Environmental Factors
Generative Artificial Intelligence (GenAI)	[61]	Absorptive capacity	Competitive pressure
Collaborative robots	[23]	Top management support, Innovativeness, Resources, Human resources	Industry pressure, External support

Table 4.4 : Additional Factors Influencing Adoption of Digital Technologies

Innovation studied	Source	Additional Factors
Cloud Computing	[56]	Technology readiness, Security concerns, Cost savings
Big Data Analytics	[96]	IT assets
B2B e-commerce	[57]	Cost reduction, Differentiation, Growth, Quality
B2B e-Commerce	[91]	Perceived cost, Organisational culture
3D printing	[97]	Technology infrastructure, Technology integration, Machine cost, Labour cost, Material cost
Digital technologies of smart manufacturing	[58]	Perceived value, Perceived costs
Industry 4.0	[60]	Cost, Market transparency, Security concerns
IIoT	[59]	IIoT expertise, Infrastructure, Cost, Security, Organisation size
Cloud-based ERP	[92]	Technology readiness, Security concern, Cost saving
Big Data	[103]	Technology competence, Technology resources
AI-powered robots	[94]	Perceived benefits, Cost issues
AI technologies	[104]	Batch size
Generative Artificial Intelligence (GenAI)	[61]	Technology readiness, Functional barriers, Phycological barriers

The conceptual model was constructed by incorporating the following key factors derived from both empirical and theoretical findings in the literature:

- Technology Factors (DOI elements): trialability, observability, compatibility, relative advantage, complexity;
- Organisational Factors: organisational readiness, suppoert from top management;
- Environmental Factors: competitive pressure, suppoert from government.

Overview of Solution Research Sub-Question (RQ4)

RQ4 aims to explore the human factors affecting cobots adoption in Australian manufacturing SMEs. In this study, as mentioned in Table 2.12 in Chapter 2, human factors are perceived as a broad concept that includes both individual and organisational attributes, roles, and capabilities that may influence cobot adoption. The literature review for this study identified several factors. This comprehensive review provides a clear understanding of the field and can serve as a practical reference to decision-makers. Based on the study purposes of this research, only factors directly aligned with the study's scope were selected for further investigation. Other factors, while acknowledged, were excluded to maintain clarity in the conceptual model. The decision to focus on specific human factors was guided by three criteria: (1) the factor must be mentioned in empirical studies only; (2) the factor must be related to the research scope and not require alternative measurements methods, such as psychometric instruments to assess variables; and (3) the factor must not rely only on direct input from workers which fall outside the research out the scope. Therefore, three human factors, whether individual or organisational, were selected as they met the three criteria in this study: innovativeness, the existence of a champion, and prior experience. Regarding innovativeness, which met the criteria for selection, it is worth noting that even when a factor was mentioned only once in the Table 2.12, it was included due to its relevance in exploring individual innovativeness, particularly decision-makers in our case, which is critical for the adoption of innovations such as cobots. This inclusion draws on Thong and Yap's seminal work [106] in IT adoption, which emphasises the significant role of CEO characteristics, particularly innovativeness, in achieving successful IT adoption. Simaially, Fink [107] asserted that small firms led by innovative CEOs are more likely to achieve successful IS adoption. As a result, the current work considers the innovativeness of decision-makers as a factor that could influence the adoption of cobots in manufacturing SMEs. The existence of a champion factor met the criteria for selection, and based on its similarity to a project champion factor, which appeared under organisational factors, both are individuals who hold a crucial role in fostering innovation and facilitating workforce adaptation during cobot adoption. Therefore, this study retained the existence of a project champion under the human dimension. The final factor, prior experience, met the criteria for selection, and it is most frequently mentioned in the literature. Drawing on the literature review and the selection criteria applied, three factors were identified under the human factor category: decision-maker innovativeness, the existence of a project champion, and prior experience. Therefore, these factors can be considered the most relevant to the cobot adoption process in this study.

Overview of Solution Research Sub-Question (RQ5)

The DOI and TOE frameworks do not present adoption barriers as a distinct group of factors. Nevertheless, defining and effectively tackling such barriers will be necessary for the successful adoption of cobots in Australian manufacturing SMEs. While one barrier, such as the complexity of technology, is acknowledged in the DOI theory, it is primarily presented as an enabler and is not categorised as a separate barrier.

Manufacturing SMEs are often slow to adopt cobots due to barriers that need to be overcome [23],[38],[108]. Hence, for researcher, presenting a distinct group of factors that inhibit cobot technology adoption in Australian manufacturing SMEs can be of great significance. Furthermore, the literature has reviewed barriers to cobot adoption in manufacturing. As presented in Table 2.11 in Chapter 2, various authors have determined these barriers based on the nature of their studies in the manufacturing context. Additionally, Australian manufacturing SMEs may face unique barriers that require further investigation. To address this, this thesis extends the DOI-TOE framework by integrating a distinct barriers dimension.

According to empirical studies in the literature, the most frequently cited adoption barriers are safety issues, lack of knowledge, and fear of job loss.

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Figure 4.6 : The 'Research Onion' (adapted from [5])

4.4 Research Methodology for Testing and Evaluating the Solution

After finalising the model, it is essential to test it rigorously. Specifically, all the factors and their relationships should be validated and confirmed. A research methodology is a set of specified principles to guide the examination and analysis of the framework's relationships [6],[109]. To validate the model, it is important to accurately select a methodology that directs the process toward specific approaches and methods for data analysis and collection [66]. [5] developed the "research onion", which illustrates the various stages of research methodology as a series of layers. Figure 4.6 visualises these layers, beginning with the broader selection of a research design (e.g., a philosophical or pragmatic foundation) and moving to more specific components such as data collection and analysis methods.

4.4.1 Methodology Selection

Qualitative and quantitative research are widely recognised in the literature as the two main methodological strands. Qualitative research is rooted in an interpretive philosophy and typically uses an inductive research approach [65]. Researchers who select a qualitative methodology typically aim to involve themselves in specific contexts to gain an in-depth knowledge of the issues being studied [67],[110]. Data collection and analyses focus on developing the perspectives and meanings of the research participants, thus enabling a comprehensive understanding of what is being studied. There are six commonly utilised qualitative methodologies: narrative research, action research, grounded theory, case study, ethnography and phenomenology [6]. Although qualitative methods are characterised by the quality and richness of the gathered data and their interpretative flexibility, they are often criticised for limitations such as generalised findings, potential researcher bias, and inherent subjectivity[67],[111].

Quantitative research often employs a deductive approach to theory building and originates from the positivist philosophy [6],[66]. It utilises numerical methods to explain and study research subjects or issues. Data collection and analysis focus on objectivity, a high level of data validity and reliability, and large-scale samples that facilitate the generalisation of results. Common quantitative methods include correlational studies, surveys, quasi-experiments, and experiments [6],[111]. Quantitative methodologies are recognised for their simplicity in explaining results, relative ease of replication and high level of precision. However, the key criticisms include a dependence on standardised procedures, which may not be suitable in particular settings, along with a static presentation of study results and an excessive emphasis on numerical data over general themes and main topics [7],[66].

This thesis focuses on identifying the factors that drive cobot technology adoption in Australian manufacturing SMEs. Currently, cobot adoption in Australia's manufacturing SMEs remains largely unexplored, although research in this area in manufacturing organisations in other countries is developing rapidly [23],[24],[54]. Furthermore, TOE and DOI are well-established theories that are often utilised to explore the factors impacting cobot adoption in the manufacturing industry [54]. Accordingly, to meet the thesis purpose, it is essential to adopt an effective strategy that integrates quantitative and qualitative methodologies to benefit from the strengths of each. Qualitative research can facilitate an understanding of cobot adoption, particularly within Australian manufacturing SMEs. In contrast, quantitative research can provide a means to examine relationships and test predetermined theories in this setting. Consequently, a mixed methods design was selected as the methodological foundation for this thesis.

Rationale for Using the Mixed Methods Approach

Mixed methods research combines quantitative and qualitative design to generate data that presents a complete 'picture' of a specific subject or issue, leading to an in-depth understanding of participants' perspectives on certain topics [112]. This concept differs from multi-method quantitative or qualitative research, where multiple methods are used within the same methodological type [5]. In this manner, mixed methods research incorporates the insights gained from both qualitative and quantitative methodologies, thereby mitigating the inherent weaknesses of each. The main reason for using a mixed methods design is to address the limitations associated with standalone methodologies [113],[114].

The mixed methodology is perceived as an effective approach in research, particularly when compared to purely quantitative or qualitative methods. Studies have argued that this methodology improves researchers' understanding of the issue [6],[7]. Furthermore, it is mentioned that applying this methodology can improve validity by integrating and comparing qualitative and quantitative analysis results [7]. According to [115], employing this methodology has several advantages: 1) it can enhance the validity of data collection instruments; 2) it enables a balanced sample size along with in-depth opinions from the participants; 3) it can achieve high levels of data integrity; and 4) it can improve research outcomes. Lastly, [66] argued that this methodology enables the efficient investigation of both static and processual information, addressing various aspects of the issues under exploration.

By selecting a mixed-methods approach, this thesis seeks to provide a comprehensive and detailed understanding of cobot adoption in Australian manufacturing SMEs, thereby enhancing existing theoretical and empirical contributions to the development of theory and testing. Although research on cobot adoption in SMEs using mixed methods is not as widespread as studies employing purely qualitative or purely quantitative designs, such single-method studies have acknowledged limitations in terms of sample representativeness, diversity, generalisability, and the need for further empirical validation [37],[46]. In addition, the two other studies [22],[23] employed a survey method with self-selection bias and still had a narrow sample. From the above-mentioned studies, only two provide a theoretical foundation by adopting the DOI and TOE frameworks, with one of these also incorporating INT, offering initial insights. However, these models were applied in their established models, without deeper adaptation to address specific operational conditions or contextual dimensions, including human factors and adoption barriers that are practically relevant to the process of cobots adoption in SMEs, and which require a more detailed investigation. Therefore, it is advisable to establish a basis for applying the mixed-methods approach in this thesis, combining in-depth qualitative understanding with large-scale quantitative analysis to validate the holistic model.

Study Design Selection

Mixed-methods research encompasses a range of designs, given its integration of qualitative and quantitative research methods. According to [7], mixed methods research is generally classified into three main types. The first, conversion design, integrates quantitative and qualitative methodologies at each phase of the study, transforming data to enable both quantitative and qualitative analyses. The second, the concurrent design, employs both quantitative and qualitative research methods simultaneously and then compares the findings. The third, the sequential design, comprises two separate phases. It begins with either the quantitative or qualitative methods for data collection and analysis; next, the findings from the first phase are enhanced or clarified using the other method in the second phase. Hence, four key categories of mixed methods designs are identified.

The first, sequential explanatory design, prioritises a quantitative methodology for data collection and analysis, using statistical tests or experimental results as a basis for understanding and knowledge development, with the qualitative methods helping to support specific findings [7]. The second, sequential exploratory design, begins a qualitative approach to gather and analyse data. After this, quantitative methodologies are employed to explain the results and examine the identified hypotheses [6]. This design is particularly suitable for refining existing perspectives and theories, developing new perspectives and confirming emerging ones. The third, convergent parallel design, involves the simultaneous and independent collection and analysis of both quantitative and qualitative data [6]. Equal importance is given to each and the findings are compared to enhance reliability and provide a comprehensive understanding of the research problem [7]. Lastly, the embedded design integrates both data types, but one plays a dominant role while the other plays a supportive and complementary role [65]. This design is used to improve the results obtained from the dominant approach. Table 4.5 summarises the mixed methodology approach applied in the research design.

Table 4.5 : Mixed Methodology Designs. Adapted from [6],[7]

Methodology	**Sequence**	**Application**	**Description**
Explanatory sequential design	Quant first, then qual.	Obtain an understanding of the unexpected findings of surveys or experiments.	Quantitative begins first, and qualitative is applied for further explanations.
Exploratory sequential design	Qual first, then quant.	Revise/develop models or theories and test them.	Qualitative begins first, and quantitative is applied to examine/test and support the results.
Convergent parallel design	Quant and qual are done simultaneously.	Attain a comprehensive understanding of the research question and improve the validity of the findings.	The methodologies are given an equal priority in investigating and explaining a phenomenon (Triangulation).
Embedded design	Primary and secondary methodology. Sequence relies on the research needs.	Enhance the study design, and clarify the findings at each stage of the analysis.	One methodology is primary/leading, and the other acts to explain/enhance the results as it develops.

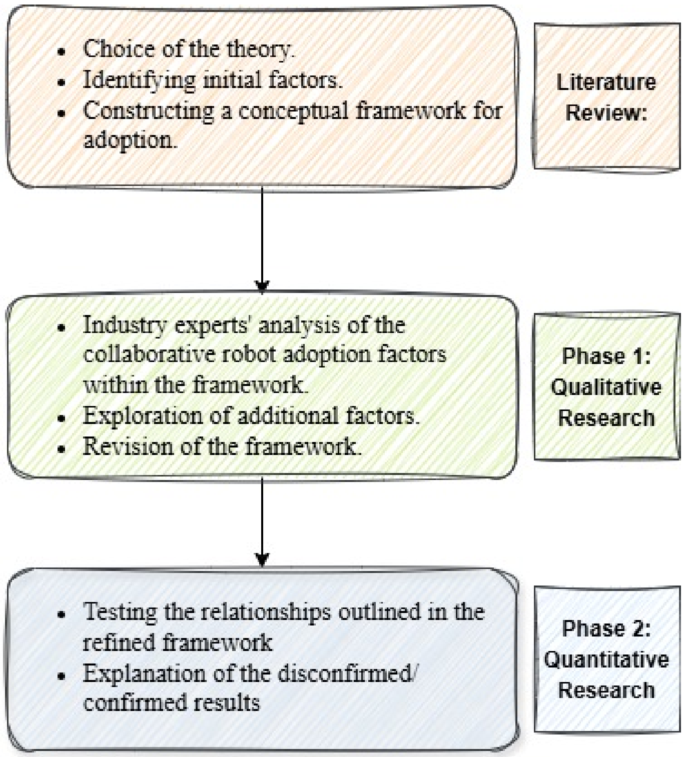


Figure 4.7 : Exploratory Sequential Research Methodology

To investigate the study questions, this thesis employs the exploratory sequential design. The primary goal is to identify the key determinants that drive cobot technology adoption in the distinct context of Australian manufacturing SMEs. This distinct approach suggests that, whereas established adoption theories could be suitable, several further factors could be revealed, and other factors identified in the literature may prove to be less significant in practice. To identify which factors could be significant, an initial qualitative study was conducted, during which industry experts provided perspectives on the usability of cobot adoption factors identified in related works and suggested additional new factors that could be beneficial. After refining the original model, a quantitative design was undertaken using a large sample to examine the relationships within the refined framework. Figure 4.7 illustrates the exploratory sequential methodology.

4.4.2 Selection of Research Strategy

A research strategy is the process used by researchers to conduct their research [116]. According to [5], the "research onion" includes several common research strategies, including action research, grounded theory, narrative inquiry, ethnography, case study, survey, and archival research. Furthermore, other strategies are also valid, such as correlational research, experiments, quasi-experiments, and phenomenology [6]. This thesis applies surveys as its main research strategy. A survey refers to the procedure of gathering information from a sample of study participants to obtain their responses to survey questions [117]. Surveys are employed across diverse applications, ranging from business fields to academic studies that explore consumer choices and marketing options. In academic fields, surveys are developed through rigorous, scientifically backed strategies for data collection methods, procedures, and sampling, contributing to minimising potential errors and reducing bias [7],[118].

In this thesis, the selection of surveys as the primary strategy is based on multiple considerations. First, surveys are widely used due to their flexibility, which allows for the use of various sampling procedures, data collection methods, and instruments [5],[6]. Second, surveys may be employed in qualitative and quantitative research types by merging open- and closed-ended questions [118],[119]. This feature is significant in the current work, since the mixed methods design was adopted. Third, surveys are widely recognised as a foundational tool in research on the drivers of human behaviour, particularly in psychology and behavioural science [120], making them suitable for examining the factors of cobot adoption in manufacturing SMEs. At the end, questionnaires are a popular and well-established tool due to their broad coverage, facilitating data collection from both large and small samples in a relatively easy manner and offering the potential to generalise the findings [6]. Accordingly, this strategy enables studies to be conducted with a larger sample of senior and middle-level managerial and IT specialists, as well as a smaller sample of industry experts in manufacturing SMEs. Additionally, this strategy helps address the budget and time constraints of this study.

4.4.3 Selection of Research Time Horizon

The required timeframe for conducting research is known as a time horizon [5]. The two classifications of time horizon, based on the research onion, longitudinal and cross-sectional. A cross-sectional timeframe comprises data collection that occurs at a specific point in time, presenting the status of the context at a single moment [6],[66]. It seeks to appropriately illustrate the research population and, therefore, comprises a diverse group of individuals. Conversely, a longitudinal time horizon assumes that a series of data sets are collected over a period, often years, followed by subsequent analysis and comparison of results [6],[66]. Although longitudinal studies can provide strong evidence and an understanding of how variables change over a period, they commonly require considerable investment in resources and time, including financial and human, to fulfil their stringent demands [66]. Furthermore, longitudinal research demands rigorous control, as respondents may change their behaviour or withdraw over time. Longitudinal research is more suitable for investigating a few key influencing factors over a period, instead of studying many factors simultaneously, as in this research. Hence, the study selected a cross-sectional time horizon to be followed based on the aforementioned reasons.

4.4.4 Research Methods

As previously discussed, this research employs an exploratory sequential methodology. The two phases that guide the process of data collection and analysis are outlined as:

- Phase 1: The objective of this phase is to investigate and understand the research framework and the relationships within the framework, which will be conducted through qualitative research.
- Phase 2: This phase seeks to examine and evaluate the output from Phase 1, which is a refined framework and its relationships, and will be conducted through quantitative research.

The subsequent sections present an overview of these two phases, which utilise different research methods for data analysis and collection.

4.5 Phase 1: Qualitative Research

This research identified a set of factors considered relevant to the cobot adoption process in manufacturing, based on a comprehensive review of the existing literature. However, qualitative research was conducted to refine the proposed framework and contextualise it for the Australian manufacturing SME sector.

4.5.1 Qualitative Data Collection and Analysis

The objective of this procedure is to refine the model in a context-specific manner by presenting new factors and removing those deemed weak or insignificant.

Qualitative Data Collection Process

In the first phase of the work, an in-depth semi-structured interview approach was conducted to acquire participants' perspectives, thoughts, opinions and views on a particular topic [6]. With semi-structured interviews, open-ended questions are arranged around specified topics. Thus, this approach is more flexible and differs from structured interviews in that it allows for new views on the issues while ensuring that the interview discussions remain within the study's narrative and align with its topics without excessive deviation from significant topics. Semi-structured interviews in this study follow a particular protocol that involves themes/topics and respective questions to meet these objectives [121]. As a result, the interview questions serve as a guide and may be asked differently by various individuals.

The selection of semi-structured interviews was based on multiple criteria. Based on a previously established framework, the interviews were applied and hence, the interview data can easily be arranged by themes. To adhere to the theoretical underpinnings of this thesis, it is essential to remain within these themes. However, it is important to allow some flexibility to enable the participants to share their opinions on a new aspect related to cobot adoption. Accordingly, these interviews are the optimal selection for qualitative data collection, as they apply themes and enable the expression of perspectives and opinions within them. The majority of limitations of these interviews, such as subjective issues and concerns about generalising the results, are addressed by applying Phase 2 of the research, which includes examining the results using statistical methods on a large scale.

Unlike quantitative research, qualitative research does not involve broadly predetermined norms for sample size. In the literature on qualitative research [122],[123], and specifically qualitative interviews [121],[124], a data saturation approach is frequently recommended to determine sample size. In qualitative research, data saturation is perceived where additional data collection no longer yields new or meaningful insights necessary for a thorough understanding of the subject being investigated [122]. By applying these recommendations, this research assesses the point of data saturation from a developmental perspective, exploring new insights and themes regarding the cobot adoption in Australian manufacturing SMEs. When no new insights are obtained throughout a particular interview, the stage of data saturation has been established.

Based on the principle of data saturation, the qualitative interview phase involved ten participants. During the interview process, recurring themes related to collaborative robot adoption in manufacturing SMEs began to emerge, and no substantially new insights were identified in the later interviews. This indicates that data saturation was achieved, suggesting that the sample size was sufficient to address the qualitative research objectives. Furthermore, the participants were selected decision-makers and technology specialists with direct experience relevant to cobot adoption, which supports the adequacy of a smaller, information-rich sample, as recommended in qualitative research methodology literature [122, 123, 124].

A sampling frame was first established in the interview phase in collaboration with the researcher's supervisors, which involved identifying a contact list of as many manufacturing SMEs in Australia as possible. The directory contained information on manufacturing SME classification (small or medium), location (state or territory), email addresses, and contact names of key personnel (e.g., owner, CEO). However, contact names were not available in certain firms. The directory was developed using government and industry sources such as the Australian Small Business and Family Enterprise Ombudsman (ASBEFO), the Australian Bureau of Statistics

(ABS), Australian Manufacturing Technology Institute Limited (AMTIL), Manufacturing Australia, Australian Industry Group (Ai Group) and commercial databases like IBIS World and Dun & Bradstreet. To achieve a representative sample that is balanced for interviewees' positions (senior and mid-level managerial/technology specialists) and the manufacturing size (small/medium enterprises), the research identified a minimum number of participants for interviews. A convenience sampling strategy was applied to recruit interview participants based on willingness and availability to participate. Although this strategy is not advisable in quantitative studies, it is regularly applied in qualitative research to balance a small sample of likely representatives of all research groups [121]. In the study sample, the key inclusion criterion was that the interviewee was a decision maker in a manufacturing SME. The study involved ten interviewees comprising individuals in managerial and technology specialist roles in Australian manufacturing SMEs. Participants involved in the interview phase must be excluded from participation in the survey phase.

Before the interview sessions, interviewees were presented with a copy of the thesis aim, the interview objectives and their rights as respondents. All interviews took place between October 2022 and January 2023 via online meetings (Zoom). Drawing on the recommendations of prior studies, a set of themes was formulated to guide the interview process. These themes encompass overall views on the potential of cobots in manufacturing SMEs, factors supporting the adoption of cobots in manufacturing SMEs (classified into organisational, external (environmental), technological, and human dimensions), and barriers to their adoption. Depending on the interviewee's response, each session was scheduled for 30 to 50 minutes, and all interviews were executed in English. Appendix A provides the interview questions. After each interview, the participants received their respective transcriptions, thus enabling them to make any necessary revisions to clarify their ideas and opinions. For data analysis, the study then utilised a revision of the transcript files.

Qualitative Data Analysis

Manual content analysis was utilised to analyse the collected qualitative transcript data. As a popularly used study technique, content analysis is well supported in the literature for its ability to systematically identify patterns, themes, and meanings within textual data [125],[126]. Given that this study builds on existing frameworks and theories, the direct content analysis approach was specifically adopted [127],[128]. Within the current work, the objective of this approach is to validate or develop conceptually a theoretical framework [128]. This aligns with the goal of this phase of qualitative research, which aims to understand the previously adopted factors with a solid theoretical underpinning by refining the research framework through the removal or introduction of other emerging factors based on interview data.

Following the approach outlined by [129], this research employs three main steps of data analysis: qualitative data reduction and organisation, data coding, and data display. Unlike conventional approaches, the direct content analysis method allows for a more structured process for analysing data [130]. For the data reduction step, the data from the transcription is coded and simplified. While new codes are developed using the conventional content analysis approach, this differs when applying a direct content research approach, which often utilises existing models and theories to develop preliminary coding categories [131]. Therefore, the proposed conceptual framework includes predefined codes derived from variables determined in this research (See 4.3.4). When qualitative data cannot be easily associated with any predefined group, it is identified as a new group, which may develop into a new factor influencing cobot adoption

After completing the first step, recurring patterns were identified in the data. For each coded factor, the frequency of mentions was observed. The factors were then analysed separately based on their occurrence, that is, those mentioned infrequently and those mentioned frequently. Factors mentioned infrequently cited were viewed as potential factors for merging with others or elimination from the model. Factors mentioned frequently were analysed for their possible influence on the adoption of cobots, considering both strength (strong, moderate, weak, or unclear) and direction (negative or positive). This process follows the application of deductive category coding [132]. To develop themes that would help inform factor-related decisions, recurring patterns identified across the interview transcripts were systematically analysed. These patterns guided decisions to integrate certain factors, eliminate certain factors from the model or retain them as standalone elements, with justifications for these decisions.

The refined HCRAM framework for cobot adoption in Australian manufacturing SMEs is a main finding of the qualitative analysis. Figure 4.8 summarises the qualitative data analysis approach.

4.6 Phase 2: Quantitative Research

To enhance the generalisability of the results, the researchers can use quantitative methods that enable them to gather a large amount of data [65]. Quantitative methods provide a high degree of objectivity and accuracy in the results, which confirms their validity and reliability. Quantitative research enables the comparison of these results with available research on the subject by employing numerical analysis and statistical methods, and allows for analyses across categories and time.

Surveys are employed as a common quantitative method for data collection. In quantitative research, an online survey is one of the most frequently applied approaches [7],[118]. Given the penetration of the internet and the development of online and digital technologies, questionnaires have become a common data collection tool [6]. According to [5],[6], online surveys are preferred as a data collection method based on the following advantages:

1. *Low Cost:* There is no need for researchers to travel to distribute the survey. Various online platforms are available to set up surveys with minimal costs;

2. *Large Number of Respondents:* Surveys can collect a large amount of data and include individuals from different backgrounds;

3. *Organisation and Structure:* Survey results can be compared efficiently, and surveys can be replicated;

4. *Data Analysis:* It may be efficiently conducted by applying consolidated statistical packages and other tools that support both inferential and descriptive statistical analysis;

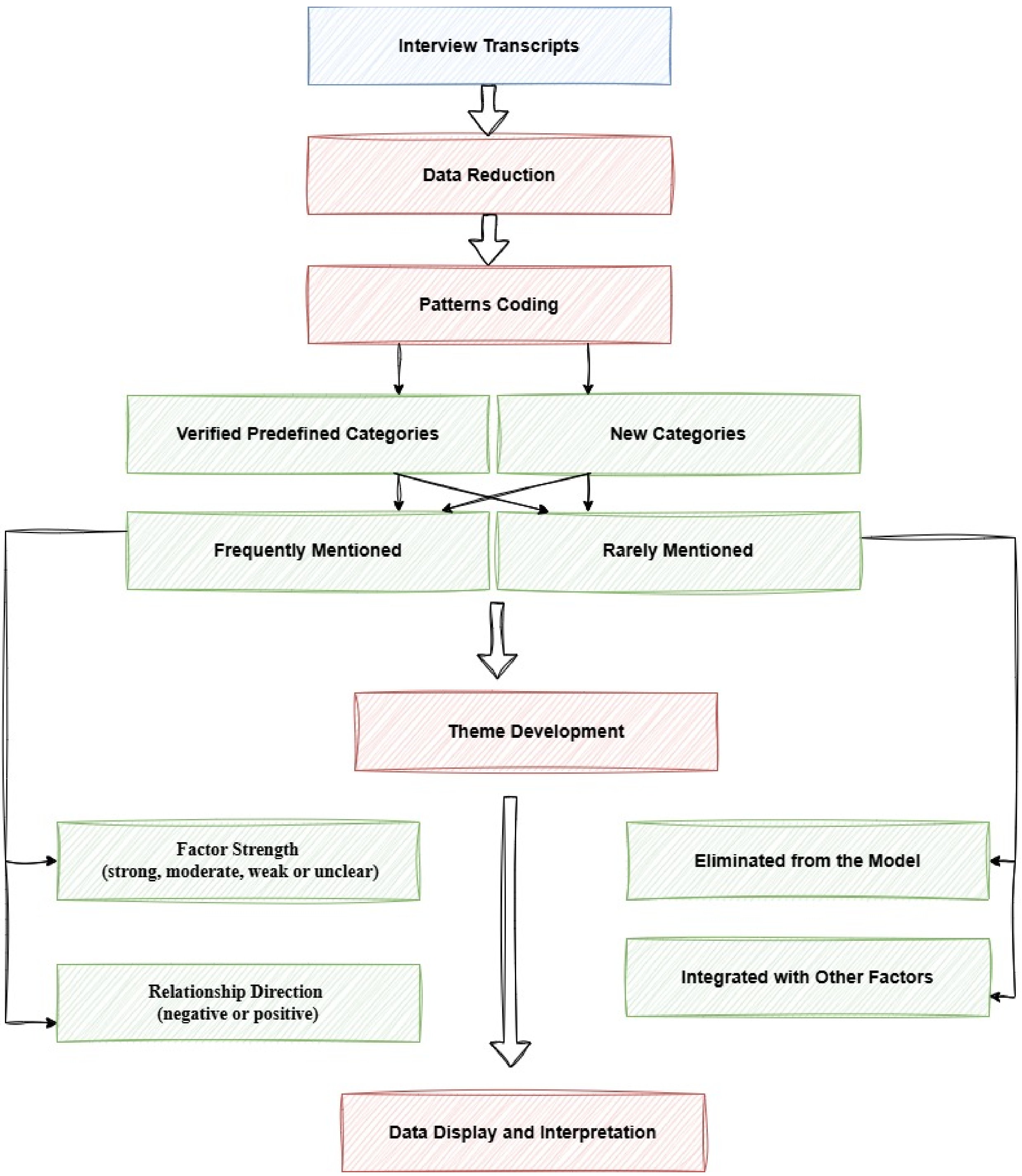


Figure 4.8 : Stages of Qualitative Data Analysis

5. *Respondent Anonymity:* Given that data collection occurs on an online platform, no personal information is shared, and survey respondents are encouraged to respond to the survey questions easily and comfortably;

6. *Reducing Bias:* To minimise personal bias in the study, surveys detach the respondents from the researcher;

7. *Data Codification:* Surveys benefit from inbuilt online tools that minimise human error in data entry and speed the process, thereby facilitating data coding and organisation.

4.6.1 Quantitative Data Collection and Analysis

The subsequent section provides the procedure for quantitative data collection, including instrument development, participant recruitment, and data analysis.

Quantitative Data Collection Process

In line with positivist research principles, a large-scale survey was regarded as the optimal method for capturing generalisable patterns and testing predefined hypotheses. The current work used a questionnaire as the main data gathering method, designed to gather insights from a large sample of managerial and IT professionals from Australian small to medium-sized manufacturing enterprises (SMEs). The questionnaire provided a structured tool for both data analysis and collection, enabling the application of statistical techniques aligned with the study's design parameters. In line with positivist research principles, a large-scale survey was deemed the most appropriate research method for capturing generalisable patterns and testing hypotheses [133]. The survey items represent the constructs derived from the research conceptual framework. To assess the interviewees' awareness of cobot technology, this study conducted a focus group comprising top-level managers from Australian manufacturing SMEs. Participants expressed limited familiarity which may be attributed to the recent emergence of cobot technology, and the limited integration of efficient applications in the SME manufacturing context. To ensure the survey participants fully understood the scope and terminology, a a summary of cobots

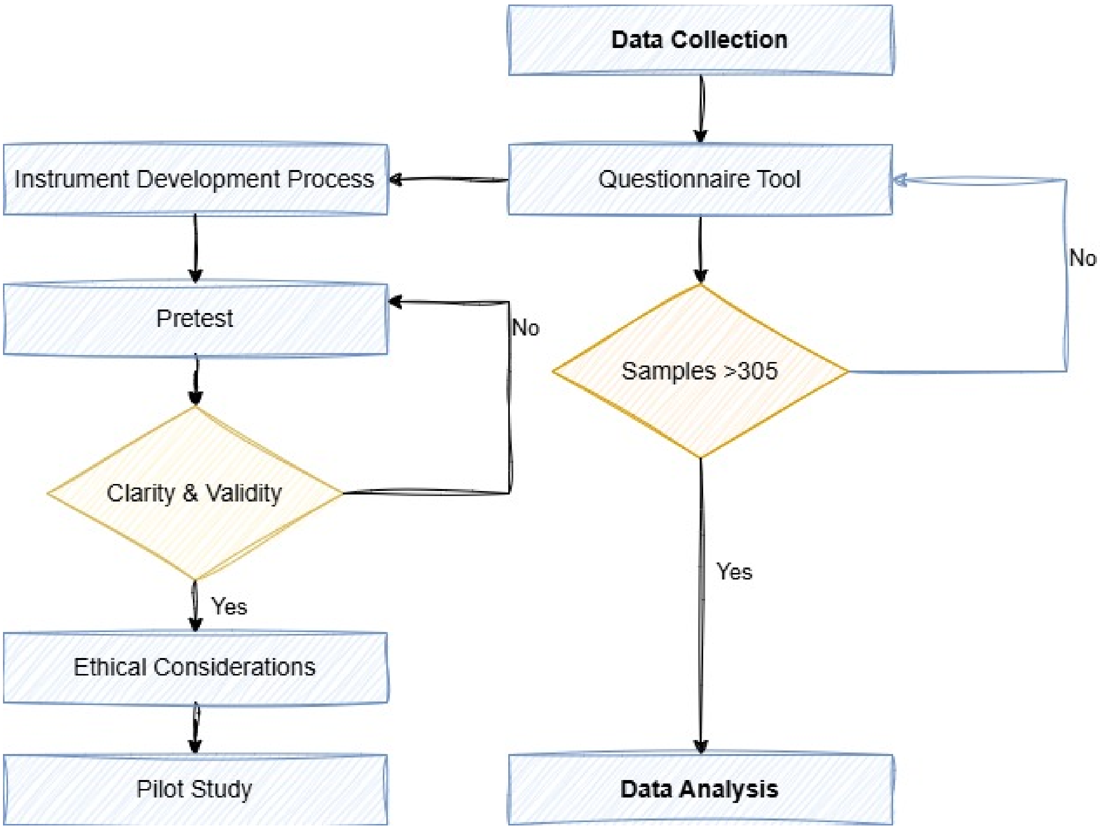


Figure 4.9 : Approach for Quantitative Data Collection

was provided on the first page of the survey. Figure 4.9 illustrates the structured approach used for quantitative data collection.

Instrument Development Process

According to [134], the proposed procedure for questionnaire development in this research comprises three steps: creating survey items, developing the scale, and testing the instrument. The details of these steps are as follows:

- Step 1: Item Creation

  The questionnaire items were developed to align with the constructs in the refined HCRAM conceptual model. Following the completion of Phase 1, the research framework was finalised. Section 7.2 presents the questionnaire instrument and the sources from which its items were derived.

- Step 2: Scale Development

In this study, the questionnaire items were aligned with the identified constructs and designed using a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). which helps ensure continuity and integrity of the data. This scale was applied, with the coding and options ranging from 1 (strongly disagree) to 7 (strongly agree). This scale was selected to ensure greater measurement sensitivity than a 5-point scale. Research suggests that 7-point scales yield higher reliability and stronger correlation with statistical significance than 5-point scales [135]. Second, data derived from a 7-point scale are appropriate for high-level analyses [136]. Third, a 7-point scale is more suitable for respondents' subjective evaluations, such as beliefs related to technology applications [137]. The respondents indicated that a 7-point scale was the easiest to use and the most accurate for expressing their views. As noted by [138], the 7-point scale provides a superior trade-off between the reliability of items and the number of discriminating points. Hence, this study employed a 7-point scale for its questionnaire design.

- Step 3: Instrument Testing

  Before distributing the questionnaire to the participants, a pre-test was conducted, representing the final stage as defined by [134]. The pre-test in this research was based on assessments offered by two small groups. Participants from the technology experts group evaluated the questionnaire items for clarity and accuracy. The other participants from the PhD candidate group checked the ease of use of the questionnaire and identified potential concerns regarding the time needed to complete the survey.

Population and Sampling

A work population consists of the full set of individuals, objects or cases that share specific characteristics that are the focus of an investigation. [139]. The target population in this thesis comprises decision makers at various managerial levels, including top-level executives (e.g., presidents, CEOs, CIOs), middle management (e.g., production managers, manufacturing supervisors, plant managers) and technology specialists (e.g., IT professionals, engineers, CTOs) in manufacturing SMEs in Australia. These individuals were selected as they are knowledgeable and responsible for implementing innovation development strategies in their organisations.

Due to the large size and indeterminate boundaries of the target population, this study employed a sample as a practical alternative. A sample represents a set of cases derived from the broader population for study purposes [140]. Research commonly distinguishes between two broad categories of sampling: probability-based methods and non-probability methods. Probability sampling is characterised by the fact that every unit in the population has a calculable and non-zero probability of selection, thereby allowing for representative inclusion. By contrast, non-probability sampling methods operate without such known probabilities, making it impossible to determine the exact likelihood of any individual being selected [140]. Probability sampling is widely adopted in research due to its capacity to enhance generalisability, uphold validity and minimise selection bias. [141]. Applying this type of sampling also requires the identification of a sampling frame, which is a defined subset of the population that includes only those members eligible for selection in the study [142]. Therefore, the same sampling frame used in the first phase 4.5.1 was employed, excluding the 10 organisations that had participated. This enables the researcher, in the second phase, to reach participants from a wide range of manufacturing SMEs. Given that manufacturing SMEs are distributed across multiple locations in Australia, the study employed a stratified random sampling strategy rather than a simple random strategy to minimise sampling error [143]. This approach was selected to ensure appropriate representation of manufacturing SMEs across geographic regions and organisational sizes.

To operationalise the stratified random sampling strategy described above, the predefined sampling frame of Australian manufacturing SMEs was organised in two stages. First, the sampling frame was stratified by state and territory to ensure national geographic coverage. Second, organisations within each geographic stratum were categorised by firm size (small or medium enterprises) to account for organisational heterogeneity within the SME sector.

Following this stratification process, survey invitations were distributed to all accessible eligible organisations within each state and size-based stratum. In each manufacturing SME, the invitation was directed to a decision maker responsible for technology or operational decisions (e.g., senior management, middle management, or technology specialists). Where only a general organisational contact was available, the contact was requested to forward the survey to the appropriate decision maker. No selective targeting or preferential inclusion of specific firms or individuals occurred beyond the stratification criteria. Consequently, each eligible SME within a given stratum was provided with an equal opportunity to participate, thereby operationalising randomness at the invitation stage. Participation was voluntary, and responses were obtained through self-selection following invitation. This description clarifies how random sampling was implemented in practice during the quantitative phase and is consistent with accepted approaches to stratified random sampling in organisational survey research.

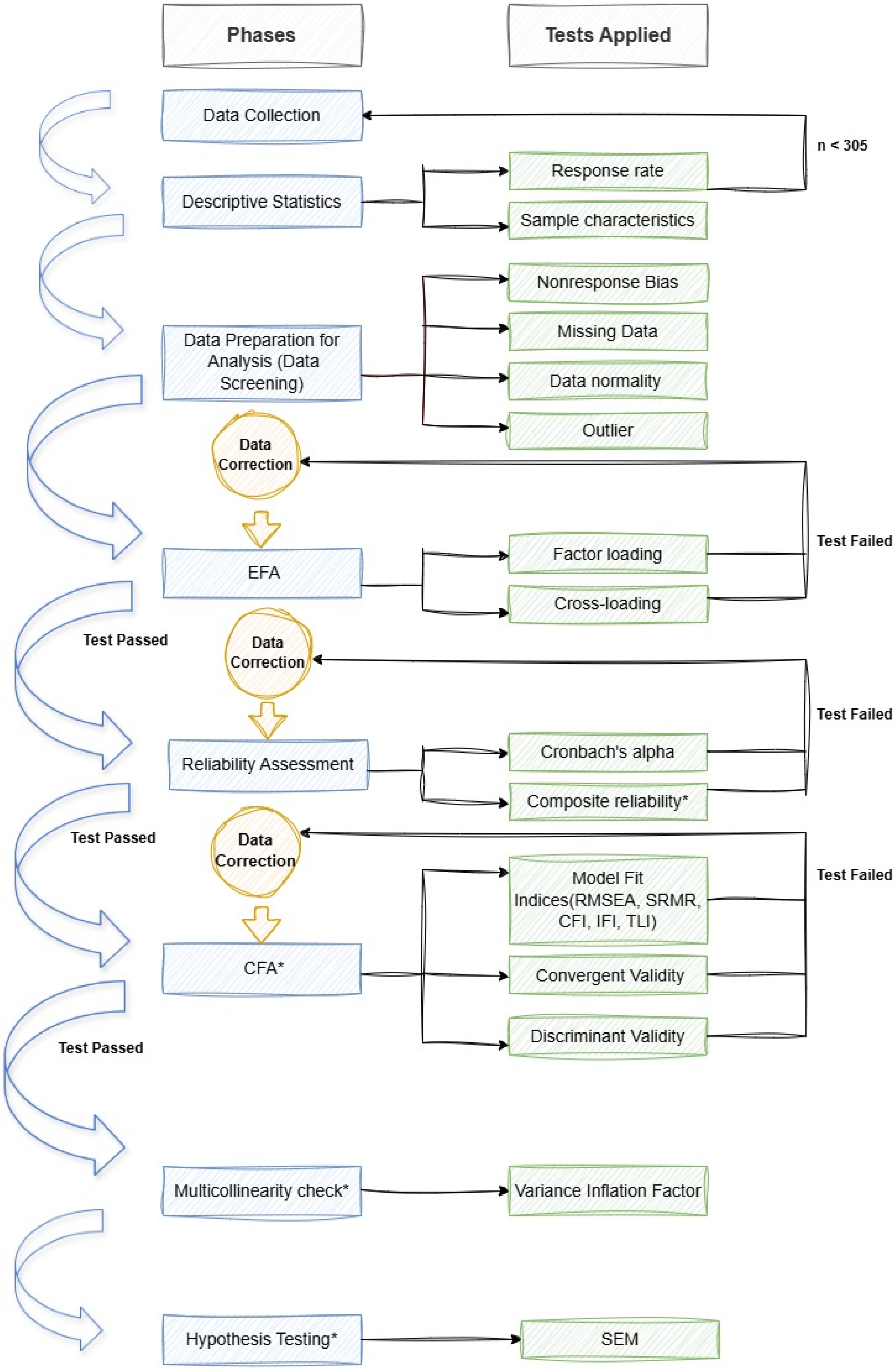
To assess validity and reliability, it is important to determine an appropriate sample size [144]. In this research, Structural Equation Modelling (SEM) served as the analytical technique for the quantitative data. According to [145], For SEM, a sample size of at least 200 respondents is generally advised when using maximum likelihood estimation. This guideline is used as a standard for statistics. A more rigorous method for determining the minimum sample size in SEM recommends that the sample should be no fewer than five to ten cases per indicator. (items) [146]. With an estimated 61 items in the model, the minimum necessary sample size ranges from 305 to 610 respondents. Similarly, following Nunnally [138], the minimum sample size is 10*n, where n represents the number of observed variables (items), resulting in a required number of respondents of 610. Thus, the research aims to engage at least 610 respondents, although a sample size exceeding 305 is considered acceptable.

Administration and Distribution

The Qualtrics platform was used to administer a pre-tested questionnaire, approved by the UTS Ethics Committee, to target and recruit decision-makers from manufacturing SMEs in Australia. Email invitations were sent to the previously identified contact lists of manufacturing SMEs, formally requesting permission to engage with eligible respondents. The email included: 1)A letter of introduction outlining the objectives of the research and requesting cooperation in recruiting participants; 2) an attached ethical approval form; 3) the researchers' contact details for further communication; and 4) A survey access link was provided. A follow-up strategy was implemented using multiple communication media (e.g., emails and telephone calls) to encourage survey completion and improve the response rate. No additional contact was made with manufacturing organisations that declined to participate.

Quantitative Data Analysis

The analysis of quantitative data was carried out with IBM SPSS Statistics version 26 and AMOS, employing a two-step process: First, descriptive statistics were generated based on responses from the participant profile section. Second, a two-phase inferential analysis was undertaken. At the initial stage of analysis, a confirmatory factor analysis (CFA) was carried out to estimate and validate the measurement model [147]. This model tests the reliability and validity of the gathered quantitative data. Internal consistency reliability was assessed using two established measures: composite reliability (CR) at a > 0.7 adequate level [148],[149] and Cronbach's alpha, with an acceptable value of ≥ 0.7 [150]. Further, the square root of average variance extracted (AVE) was applied to test discriminant validity [148],[149]. Lastly, the non-response bias test was used by applying a series of t-tests [151]. Following this, to evaluate the hypothesised relationships, the structural model was estimated. An evaluation was required to establish if the model corresponded to the structural associations present in the dataset. To assess model fit, several widely used indices were employed: root mean square error of approximation (RMSEA, ≤ 0.1), Tucker-Lewis index (TLI, ≥ 0.9), incremental fit index (IFI, ≥ 0.9), standardised root mean residual (SRMR, ≤ 0.1) and comparative fit index (CFI, ≥ 0.9) [148],[152],[153]. Moreover, to ensure a goodness of fit, some items were deleted and scales were modified as needed. Finally, path analysis was performed within the structural model to evaluate the study's hypotheses, using a 5% significance threshold (p ¡ 0.05). Figure 4.10 visualises all the stages of the quantitative analysis.



** for tests applied in AMOS; other tests applied in SPSS software*

Figure 4.10 : Stages of Quantitative Data Analysis

4.7 Ethical Considerations

Prior to data collection, the required ethics applications were disseminated to the UTS Human Research Ethics Committee (HREC) (Reference No. ETH22: 7564 for Phase 1 and Reference No. ETH24: 9468 for Phase 2) to obtain ethical approval. This research adhered to the recommended procedures and practices, including the ethics code, the protection of anonymity, the right of participants to withdraw, and the voluntary nature of participation. The aim and objectives were also clearly presented in the consent forms. The consent forms for Phase 1 and Phase 2 are provided in (Appendix B) (Appendix C).

4.8 Summary

This chapter discussed the proposed solution for addressing the study questions and outlined the selected methodology. The current work adopted a six-phase design science approach. The research solution began with the selection of the underlying theoretical frameworks for the cobot technology adoption model. As this thesis focuses on the organisational level and its aim is to incorporate additional variables, the TOE [4] and the DOI [63] were chosen as theoretical foundations. These theories are well validated at the organisational level and offer the flexibility to remove or add contextual variables. They were extended in this study by integrating two additional dimensions: the human dimension and adoption barriers.

This study followed a mixed research methodology to examine and validate the proposed model and justify its selection. In Phase 1, the model is presented to several industry experts for initial evaluation through semi-structured interviews. The outcome is a refined model that considers a final product with some factors added or removed. In Phase 2, the adoption model is validated using a large-scale questionnaire to assess its effectiveness in predicting cobot adoption among Australian manufacturing SMEs. For both phases, the collection and analysis methods are discussed. Chapter 5 presents the proposed HCRAM model of cobot adoption and its relationship to the associated variables.

Chapter 5

A Holistic Collaborative Robot Adoption Model (HCRAM) for Australian Manufacturing SMEs

5.1 Overview

Chapter 5 introduces the initial model of the Holistic Collaborative Robot Adoption Model (HCRAM), developed to describe and support the adoption of collaborative robots (cobots) in manufacturing SMEs. The development of HCRAM was grounded in an extensive analysis of theoretical and empirical studies on cobot adoption. The model combines the TOE framework and the DOI theory, supplemented by a human dimension context and a distinct dimension of adoption barriers to represent the specific conditions of manufacturing SMEs, as outlined in section 5.2. In section (5.2.1 - 5.2.5), each dimension represents a set of factors hypothesised to influence the process of cobot adoption. These factors are described in detail, along with their proposed roles in the adoption process

5.2 HCRAM Model and Hypotheses Development

The proposed HCRAM model is grounded in the combination of the extended DOI-TOE framework, which posits that the cobot adoption process in manufacturing SMEs is influenced by five contextual dimensions: technology, organisation, environment, human, and adoption barriers, as illustrated in Figure 5.1. Given the limited research applying DOI and TOE to cobot adoption in the manufacturing context, the study was extended to include studies on the adoption of other advanced manufacturing technologies, supported by core propositions within DOI and the TOE, as outlined in Chapter 4. This strengthens the theoretical foundation of the model's factors. Accordingly, the factors selected for the HCRAM established a set of proposed factor relationships, identified through a review and analysis of empirical studies in chapters (2 and 4). In line with this, the operationalised and corresponding impacts of each factor on cobot adoption are presented in Figure 5.1.

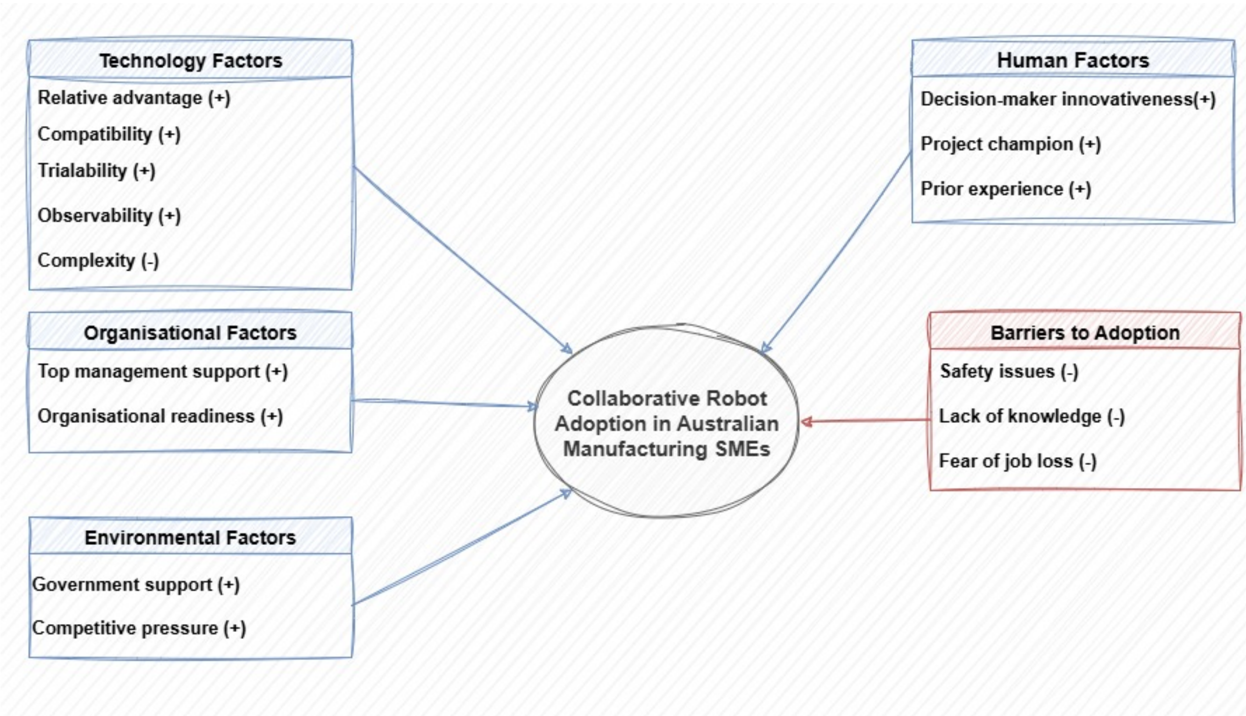


Figure 5.1 : Holistic Collaborative Robot Adoption Model (HCRAM): A Conceptual Model for Australian Manufacturing SMEs

5.2.1 Hypotheses in the Technology Context (Hypothesis 1)

Technological attributes play an important role in the adoption process. Adoption is more likely when the technology offers clear advantages and operational improvements that exceed the costs and resources required for implementation. Following the DOI theory [3], this research considers the influence of five established attributes, each expected to influence the decision to adopt cobot in Australian manufacturing SMEs.

Relative Advantage: This represents the level to which an innovation is evaluated as enhancing organisational performance or outcome [63]. For manufacturing SMEs, this may indicate the degree to which cobots are expected to enhance productivity, quality or flexibility compared with current technologies or approaches. These potential benefits are weighed against the costs and challenges of adoption, which may be financial or non-financial [3]. According to [154], this feature represents one of the most frequently examined attributes of innovation in studies of IT adoption, with the majority of firms recognising its strategic importance. Within the cobot context, two recent empirical studies highlighted the significance of perceived technological relative advantage in large manufacturing firms in Portugal and France [24] and Chinese SMEs [54]. However, a survey of Portuguese manufacturing SMEs by [23] found this factor had no significant impact, suggesting that the results may be due to resource constraints. In studies on manufacturing context, several researchers demonstrated the positive role of this attribute in the adoption of cloud computing in Portugal [56], and in leagile manufacturing systems [105]. Similarly, in the SME manufacturing context, it was imperative in the adoption of several technologies, including its role in B2B e-commerce across four levels in Egypt [57], 3D printing in Taiwan [97], Industry 4.0 in Japan [60], IIoT in India's auto-component sector [59], and cloud-based ERP systems in Nigeria [92]. From the discussion above, and drawing on the majority of empirical findings in the literature, the hypothesis suggests that:

Hypothesis 1a: Relative advantage has a positive influence on collaborative robot adoption in manufacturing SMEs.

The second attribute within the technology context is **compatibility**, it is characterised as the level to which an innovation is aligned with the adopter's main values, established routines, prior practice, and operational requirements [63]. Low compatibility between a new technology and the organisation's prevailing norms and practices tends to impede adoption [155]. However, when an innovation is well aligned with existing technologies and processes, it generally facilitates adoption decisions [4]. Given that needs and values vary across organisations and industries, compatibility is a critical attribute in adoption decisions. Regarding the cobot context, one study conducted by [23] found no significant improvement associated with this attribute. In contrast, other researchers identified the importance of compatibility during the adoption process in large firms [24] and SMEs [54]. In the manufacturing context, some researchers noted that compatibility had no significant effect within their specific study settings [56],[57]. Conversely, others regarded this attribute as being consistent with current organisational needs and requirements [58],[59],[92],[94],[105]. Given that cobots represent a new technology, further investigation of this attribute, particularly within the Australian manufacturing SME context, should be considered. From the preceding discussion and drawing on the majority of empirical findings in the literature, the hypothesis suggests that:

Hypothesis 1b: Compatibility has a positive influence on collaborative robot adoption in manufacturing SMEs.

Trialability: Within the framework of the DOI, trialability refers to the extent to which potential adopters can test an innovation on a limited scale before committing to full-scale implementation [3]. When firms have opportunities to pilot test at a low cost, trialability can reduce uncertainty, make benefits more observable, and increase the likelihood of adoption. According to DOI theory, innovators and early adopters tend to place greater emphasis on trialability, and its practical influence often grows as technology matures and piloting becomes more feasible [3]. Seminal work identified trialability as an important attribute that enables the adoption of IT innovations [156],[157]. In one case, discussed by [46], one company initially installed a single cobot to enable employees to adjust to its presence. This approach proved successful and became standard practice within the firm. This demonstrates the importance of conducting an initial trial, consistent with the specific structural and functional characteristics of an organisation. In the context of cobots, the importance of trialability is highlighted in two recent works: one conducted in large French and Portuguese manufacturing firms [24] and another in Chinese SMEs [54]. From the discussion above, the hypothesis suggests that:

Hypothesis 1c: Trialability has a positive influence on collaborative robot adoption in manufacturing SMEs.

Observability: In the DOI theory, it is characterised as the visibility of both the process and the results of innovation adoption, enabling others to identify and evaluate its impact [3]. The DOI posits that innovations with readily observable and tangible outcomes tend to diffuse more rapidly. Observability is classified as a main attribute in the implementation of IT innovation [156],[157]. In the context of cobots, observability is perceived as the viability of use and outcomes that support adoption in large Portuguese and French manufacturing firms [24], as well as in Chinese manufacturing SMEs [54]. From the preceding discussion, the hypothesis suggests that:

Hypothesis 1d: Observability has a positive influence on collaborative robot adoption in manufacturing SMEs.

Complexity: This factor represents the level of perceived challenge in understanding, adapting, and effectively implementing an innovation [4]. The likelihood of adopting a new technology is enhanced when it is perceived as straightforward to understand and operate; conversely, when innovations are presented as difficult to utilise, it reduces the likelihood of being accepted. [158]. When adopting innovative technologies, it is imperative that decision makers consider this factor and the extent to which the innovation will apply. One study noted that during cobot implementation, repeated programming and configuration workload can be seen as a challenge, highlighting the role of complexity during operation and troubleshooting [46]. Within the context of cobots in large manufacturing firms [24], this factor is classified as a standard technological factor. The qualitative findings of this study revealed that six interviewees did not perceive cobots as complex, whereas two respondents considered them too complex. Another recent work [22] identified complexity as one of the most significant factors negatively influencing cobot adoption in Chinese manufacturing SMEs. In the manufacturing context, this factor is not seen as important in the adoption of cloud-based ERP [56],[60]. However, it is among the most frequently cited factors exerting a negative influence on technology adoption [104],[105]. Another study found that it was perceived as negative at the fourth level when examining B2B e-commerce in Egyptian manufacturing SMEs [57]. Overall, it is noteworthy that, regarding cobots, particularly in manufacturing SMEs, the decision to adopt should consider the complexity of tangible workplace transformation, which requires mechanical integration, programming skills, and workforce adaptation. This would be valuable when adopting cobots in Australian manufacturing SMEs. From the preceding discussion and drawing on the majority of empirical findings in the literature, the hypothesis suggests that:

Hypothesis 1e: Complexity has a negative influence on collaborative robot adoption in manufacturing SMEs.

5.2.2 Hypotheses in the Organisational Context (Hypothesis 2)

Although technological attributes influence adoption, adopters must also be prepared for integration. Ensuring the consistency of new technologies with established processes and strategic priorities requires organisational change, which introduces difficulties for management [159]. Consequently, the organisational context is relevant to successful adoption. In this study, two critical determinants within the organisational context are examined: readiness and top management support are selected given their likely influence on cobot adoption in Australian manufacturing SMEs, as outlined in the TOE framework [4].

Top management support: This refers to the extent to which senior leaders are committed to the technology and view it as advancing the organisation's strategic objectives [7]. Senior leaders enhance the effectiveness and quality of new solutions by providing strategic direction, a clear vision and mitigating internal resistance [160]. This factor is perceived as an imperative in the cobot context, as their active involvement promotes an effective adoption process [22],[23],[24],[36]. Within the manufacturing context, one study found that support from top management was not a critical factor [56]. However, several studies indicated that this factor was associated with a greater likelihood of IT adoption [59],[60],[91],[92],[97]. From the preceding discussion and drawing on the majority of empirical findings in the literature, the hypothesis suggests that:

Hypothesis 2a: Top management support has a positive influence on collaborative robot adoption in manufacturing SMEs.

Organisational readiness: This is regarded as a prerequisite for adoption, encompassing the processes, structures and organisational culture necessary to facilitate adoption [161],[162]. In the cobot context, two recent studies emphasised the significant role of top management [24],[54]. When top management support is limited, the risk of delayed use increases, and the expected benefits are diminished. Similarly, in the manufacturing context, researchers confirm the relevance of this factor in the adoption of 3D printing [97] and the IIoT [59]. From the preceding discussion, the hypothesis suggests that:

Hypothesis 2b: Organisational readiness has a positive influence on collaborative robot adoption in manufacturing SMEs.

5.2.3 Hypotheses in the Environmental Context (Hypothesis 3)

It comprises factors external to the organisation and influences the process of innovation adoption [4]. External factors are significant because they shape adoption decisions through external pressures and are largely beyond organisational control; as such, they need to be addressed rather than avoided. Such factors, when not effectively managed, can limit an organisation's ability to counter their impact. The external context is understood as a set of environmental enablers that influence cobot adoption decisions, as defined by the TOE framework. In this thesis, government support and competitive/peer pressure are considered potential factors that may facilitate the adoption of cobots in manufacturing SMEs.

Government support: It influences the willingness of organisations to adopt new technology. Governments can foster innovation by enhancing IT infrastructure, supporting technology, promoting initiatives, and strengthening R & D for organisations through funding [163]. In the context of cobots, several studies confirm the government's potential importance but also identified an implementation gap. In Chinese SMEs manufacturing, [54] reported that SMEs require support due to resource constraints; however, current policies fail because they target large firms rather than addressing the barriers faced by SMEs. In France and Portugal, large firms identified government agency support as the most influential external factor, emphasising their role in the regulatory environment and the development of IT infrastructure as critical elements of innovation diffusion [24]. In the manufacturing context, research identified this factor as significant for prospective adopters considering the adoption of cloud-based ERP systems [92] and B2B e-commerce adoption [91]. Notably, identifying whether Australian government support mechanisms effectively address the barriers faced by SMEs in adopting cobots would provide valuable insights for facilitating the adoption process. From the preceding discussion and drawing on the majority of empirical findings in the literature, the hypothesis suggests that:

Hypothesis 3a: Government support has a positive influence on collaborative robot adoption in manufacturing SMEs.

Competitive pressure: From a broader perspective, competitive pressure refers to the influence exerted by peers, business partners and various institutions in promoting the adoption of IT [164]. This pressure may influence organisations to adopt innovation to enhance integration or ensure compatibility with modern systems [161]. This is particularly evident when competitors hold a dominant position and the organisation has a high level of dependence on them, making technology adoption more likely as a means of preserving competitiveness. According to [54], market maturity and geographical limitations in a single province in China were not perceived as critical, despite its classification as an important external influence. In contrast, [24] found that this pressure significantly influences adoption intention in Portugal and France. Several studies in the manufacturing context confirmed the significance of this pressure in the adoption of technologies [57],[59],[91],[97],[105]. Given that this study focuses on manufacturing SMEs across Australia, covering diverse regions and varying market conditions, the role played by this factor may offer important insights into the cobot adoption process in these enterprises. From the preceding discussion and drawing on the majority of empirical findings in the literature, the hypothesis suggests that:

Hypothesis 3b: Competitive pressure has a positive influence on collaborative robot adoption in manufacturing SMEs.

5.2.4 Hypotheses in the Human Context (Hypothesis 4)

In this study, the human context is considered a distinct and specific dimension. As discussed in Chapter 2 and Chapter 4, the human factors examined in this study encompass both individual and organisational roles and capabilities that may influence the adoption process. The research suggests that the human context involves the following variables: innovativeness of decision-makers, the presence of a project champion and prior experience. These variables are classified under human factors, which are understood to facilitate the adoption of cobot technology in Australian manufacturing SMEs.

Decision-maker innovativeness: This factor is associated with individual-level attributes of the decision maker, particularly their cognitive style [165]. In general, innovativeness refers to a willingness to follow new approaches and involves how individuals process information, make decisions, and address challenges [165],[166]. Within the SME context, researchers found that small firms led by an innovative CEO are more likely to achieve successful IS adoption [107]. Similarly, the work in [165] indicated that an organisation's openness to new ideas is a crucial factor in the adoption of innovation. A major obstacle to innovation adoption is resistance from decision-makers [167]. Cobot technology represents a recent advancement in information technology. Thus, it is important to assess whether decision-makers can adapt to and readily embrace technological change, as this has been proposed to have a positive influence on the adoption of new technology, such as cobots [106]. Within the cobot context, a recent study by [36] demonstrated the significant impact of innovativeness among management staff in Russian manufacturing companies.

Drawing on the importance of this factor, as evidenced in seminal IT adoption research and a recent work in the cobot context, it is expected that the innovativeness of decision makers will promote cobot adoption in Australian manufacturing SMEs. From the preceding discussion, the hypothesis suggests that:

Hypothesis 4a: The innovativeness of decision-makers has a positive influence on collaborative robot adoption in manufacturing SMEs.

A project champion: A project champion is an individual who plays a essential role in promoting innovation, and is characterised by heightened innovativeness, a strong achievement orientation and a greater willingness to take risks [168]. The radical transformation occurring in manufacturing today, such as the introduction of human-robot collaboration, brings changes not only from technological and production perspectives but also in relation to human factors. In times of transformation, the presence of a champion is important to support the workforce and facilitate the implementation of new initiatives [169]. The existence of a champion as a human enabler is important in human-robot collaboration. An empirical work employed in a larger manufacturing firm in the UK [20] identified a process champion as a key organisational human enabler. A recent qualitative study [24] highlighted the role of a project champion in influencing cobot adoption.

In this study, both terms, project champion and process champion, are used to refer to individuals who actively advocate for and support technological innovations. The existence of a project champion is expected to facilitate cobot adoption in Australian manufacturing SMEs. From the preceding discussion, the hypothesis suggests that:

Hypothesis 4b: The existence of a project champion has a positive influence on collaborative robot adoption in manufacturing SMEs.

Prior experience: This variable reflects the degree to which the user view the current practice as closely linked to their prior experience [69]. Within the DOI theory [3], user adoption behaviour is influenced by prior engagement with previous innovations. With regard to cobots, one study [37] found that past experience with automation can foster trust and willingness to engage. Another study [30] highlighted that workers with experience in human-robot collaboration tend to have more realistic expectations and experience less uncertainty. Furthermore, a study by [56] identified prior experience as a positive factor in improving perceptions of usefulness and readiness. From the preceding discussion, the hypothesis suggests that:

Hypothesis 4c: Prior experience has a positive influence on collaborative robot adoption in manufacturing SMEs.

5.2.5 Hypotheses for Adoption Barriers (Hypothesis 5)

Although this technology offers potential advantages for manufacturing, several barriers may hinder its wider adoption. According to the DOI theory [3], one barrier embedded within its conceptual framework is complexity. In contrast, several studies on cobot adoption that do not apply the DOI theory generally overlook this aspect. Therefore, the current study focuses on the most frequently cited barriers in the cobot literature and presents these barriers within a distinct categories referred to as barriers. This could provide a practical step forward, enabling decision makers to adopt a targeted approach to addressing these barriers.

Safety issues: Safety in cobots extends beyond traditional industrial automation, in which caged robotic systems relied primarily on physical barriers as the primary protection mechanisms [29],[33]. The main focus is on preventing immediate physical harm by implementing collision prevention and system reliability measures. Operational safety in cobots requires the integration of specific technical elements, such as force monitoring, passive compliance and overload detection [41]. One study identifies mediated safety as one of the most significant barriers to cobot adoption, due to the lack of clarity regarding relevant metrics and standards [26]. Similarly, work by [15] identified safety as the main barrier to cobot adoption, emphasising the need for any interactive technology to demonstrate a positive user experience during the early stages of adoption. Another study conducted in Western Sweden SMEs by [38] also highlighted safety as a key challenge in cobot adoption, describing it in terms of the risk of injuries arising from exposure and collisions during human-robot collaboration. Furthermore, a study of European manufacturing SMEs by [46] emphasised the difficulty of ensuring safety in these firms. The study also noted that risk assessments often result to a reliance on suppliers for safety assurance. From the preceding discussion, it is expected that the safety issues may negatively affect the adoption of cobots, hence the hypothesis suggests that:

Hypothesis 5a: Safety issues related to cobots have a negative influence on collaborative robot adoption in manufacturing SMEs.

Lack of knowledge: In the DOI theory [3], technological knowledge is a key attribute that differentiates between adopter classifications. Early adopters and innovators tend to gain knowledge and understand the advantages of an innovation more rapidly, positioning them as the first to adopt it. As knowledge advances, additional adopter classifications emerge throughout the diffusion process. Therefore, insufficient knowledge is often regarded as a primary barrier hindering the diffusion of technology, including cobots [15],[26]. Similarly, [46] emphasised that the lack of integration of knowledge was considered a barrier. In a subsequent study, [25] identified knowledge-related issues primarily as training needs, understanding robotic functionality and basic computer skills. Furthermore, it identified a knowledge gap regarding business benefits, technology awareness, and market understanding, highlighting the need to enhance cobot knowledge among employees for successful implementation. From the preceding discussion on the relation between knowledge and its use, it may be argued that insufficient knowledge poses an obstacle to cobot adoption. Accordingly, the hypothesis suggests that:

Hypothesis 5b: A lack of knowledge related to cobots has a negative influence on collaborative robot adoption in manufacturing SMEs.

Fear of job loss: Concerns about job displacement and limited career progression may discourage employees from supporting the introduction of cobots [46]. This may create feelings of anxiety and uncertainty, thereby reducing openness to the organisational change that accompanies their adoption [46]. Researchers in the cobot context have recognised this issue and identified it as a significant barrier to adoption. The work by [25] identified fear of job loss as the main challenge at the employee level in the African manufacturing context, encompassing concerns about redundancy, retrenchment, and rising unemployment. Likewise, [32] identified this barrier as a key determinant impeding cobot acceptance in German manufacturing, emphasising that addressing it requires effective internal communication strategies. Finally, [46] highlighted fear of job loss as a cultural barrier contributing to organisational resistance to change. From the preceding discussion, it is expected that the fear of job loss may negatively affect the adoption of cobots, hence the hypothesis suggests that:

Hypothesis 5c: Fear of job loss has a negative influence on collaborative robot adoption in manufacturing SMEs.

5.3 Summary

Chapter 5 introduced the proposed HCRAM for manufacturing SMEs regarding an extensive review of empirical works on adoption in manufacturing SMEs. This model comprises five dimensions and 15 factors that may influence the cobot adoption process, each justified about its specific role. The hypotheses were proposed, based on this framework, to investigate the relevance and contribution of five contexts to cobot adoption in manufacturing SMEs.

Chapter 6 details the findings from the model proposal and its subsequent evaluation, conducted with technology specialists and manager-level participants from both top and middle management.

Chapter 6

Phase 1: Qualitative Research

6.1 Overview

The detailed outcomes of the qualitative data were gathered from interviews with ten industry decision-makers. It begins with an overview of the interview participants and their positions in the industry (Section 6.2). The aims of phase one were to firstly, determine the most promising application areas of collaborative robots for Australian manufacturing SMEs; and secondly, uncover the key factors in the adoption process. Section 6.3 presents both of these aims in detail in the data analysis and results of the Interviews. It also provides a refined HCRAM conceptual model of collaborative robot adoption, which contains newly proposed factors based on the participants' views and excludes those factors that the participants regarded as insignificant (Section 6.4). Finally, the chapter concludes with a summary of the important results (Section 6.5).

Portions of Chapter 6 have been published as follows:

- M. Haddas and F.K. Hussain, "Technology Factors Affecting Australian Manufacturing SMEs Adoption of Collaborative Robot Technology: A Qualitative Interview Study,". In *Proceedings of the 43rd International Business Information Management Association Conference (IBIMA)*, Madrid, Spain, June 2024.
- M. Haddas and F.K. Hussain, "Human Factors Influencing Australian Manufacturing SMEs' Adoption of Collaborative Robots: A Qualitative Study. In *Advanced Information Networking and Applications: Proceedings of the 39th International Conference on Advanced Information Networking and Applications (AINA-2025)*, vol. 7, Cham, Switzerland: Springer, 2025, pp. 154-164.

6.2 The Interview Participants

The research interviews were conducted with key decision makers, including managerial and technology specialists from SMEs in Australian manufacturing. Following the methodological guidelines in [121],[124], the study employs a data saturation approach. By the tenth interview, the analysis indicated that data saturation was reached, as no new themes or meaningful insights emerged. Consequently, the data were considered appropriate for the analysis phase.

General information about the interview participants is provided in Table 6.1. The interview sample was balanced with respect to participants' positions and the classification of their manufacturing organisation (small/medium) based on employee numbers. The sample consisted of ten participants in both high-level and medium-level positions, with five holding managerial roles and five being technology specialists. Three of the interviewees represented small manufacturing, and seven represented medium manufacturing. The participants' knowledge level regarding collaborative robots was categorised into two levels: six interviewees characterised their knowledge as excellent, great, or good, while the remaining rated their knowledge as moderate, sufficient, or reasonable. Thus, the interviewees had an adequate level of expertise with collaborative robots for the study's purpose.

Table 6.1 : An Overview of the Interview Participants

N	Interviewee's Code	Interviewee's Position	Industry	Size (No. of employee)	Classification	Level of Collaborative Robot Knowledge
1	P1	Chief Technical Officer (CTO)	Appliance Manufacturing	100	Medium	Good
2	P2	Technical Support Specialist	Textile Manufacturing	126	Medium	Good
3	P3	Chief Executive Officer (CEO)	Furniture Manufacturing	76	Medium	Good
4	P4	Operations Manager	Paint manufacturing	19	Small	Some
5	P5	IT manager	Textile Manufacturing	198	Medium	Good
6	P6	Production Manager	Paper Product Manufacturing	196	Medium	Good
7	P7	Process Engineer	Sporting Goods Manufacturing	18	Small	Some
8	P8	General Manager	Camping equipment Manufacturing	16	Small	Some
9	P9	Automation Engineer	Plastic Product and Packaging	188	Medium	Some
10	P10	General Manager	Metal Product Manufacturing	98	Medium	Good

6.3 Interview Data Analysis and Findings

In this phase, the three-step process recommended by [129], as outlined in Chapter 4 was used for the analysis. The two types of analyses in this research are provided to support the thesis objectives and fulfil the requirements for gathering and analysing the interviews. The first section describes the experts' perceptions with regard to the promising application areas of collaborative robots for Australian manufacturing SMEs. In the second section, independent constructs and dimensions relevant to collaborative robot adoption are descriptively conceptualised to uncover the possible connections among the study's constructs during the adoption process.

6.3.1 Experts' Views on Promising Collaborative Robot Applications

The interviews with participants started with an explanation of the topic and the aim of the interview. This was followed by a discussion that focused on the participants' views in terms of the use of cobot technology and the extent to which it is applied in Australian manufacturing SMEs. A total of nine participants discussed this subject matter. The majority indicated that the integration of collaborative robots is still in its early stages, specifically in manufacturing SMEs. The adoption level was described as follows: 'very low' (4 participants), 'somewhat' (2 participants), and 'in its beginning' (3 participants). One participant, P6, reported high adoption rates in large manufacturing stating, "as you see, there are high adoption rates in large manufacturing environments". In contrast, P10 commented on reasons why SMEs have lower adoption rates, stating, "we are generally pretty slow to adopt in SMEs, in Australia, [...] lack of investment in advanced technologies, inadequate technical preparation of our employees".

Following this, the participants were asked about the possible promising application areas for cobots in Australian manufacturing SMEs to identify the most viable areas for further investigation. Table 6.2 presents the identified codes from the analysed transcripts for promising areas of application dimensions. According to the review of the existing literature, assembly was identified as the most frequently cited application. Moreover, Universal Robots - recognised as a pioneer in collaborative robots-

Table 6.2 : List of Codes for the Collaborative Robots Promising Areas of Application Dimensions

Code	Meaning	Frequencies
PAA	**Promising Application Areas**	**10**
PAA-ASS	Assembly	10
PAA-MAH	Material Handling	8
PAA-MAT	Machine Tending	8
PAA-QUI	Quality Inspection	6
PAA-WEL	Welding	4
PAA-MAR	Material Removal	3

also emphasised assembly as an application, and seven other potential applications were identified. However, two of the suggested applications (finishing and dispensing) were not mentioned by all interviewees. The six promising areas of application are discussed in the following. The most commonly discussed application among interviewees was **assembly**, which was mentioned by all respondents. They focused on how collaborative robots help to reduce fatigue and physical strain on human workers in assembly lines. With respect to this, some interviewees' responses were[1]:

One important thing to consider is that integrating cobots into an assembly line will significantly reduce the incidence of musculoskeletal injuries and fatigue risk. (P3)

... I mean, collaborative robots can be quickly adapted to assemble diverse parts; which will be especially beneficial for most SMEs with different product lines. (P4)

In the assembly line, workers still suffer continuous physical strain; collaborative robot technology will assist in keeping the processes working smoothly and reduce the strain... There is a great time for employees to rest, which is one big advantage. (P5)

Part insertion and fastening, for example, are usual applications in assembly tasks, and the use of a collaborative robot is essential here... We need careful attention to

[1]All direct quotes from the interview transcripts, and may contain errors or non-academic expressions.

insert different components, like circuit boards, and then secure them with screws. The adoption of collaborative robots enables organisations to make better use of employees' skills by reducing time spent on repetitive tasks. (P6)

Another commonly discussed application was **material handling**, which was mentioned by 8 of the 10 interviewees. The participants particularly spoke about such areas of material handling as bin picking, palletizing and depalletizing products:

I think it is an amazing technology because it can handle even delicate items in bin picking. The capability of collaborative robots to perform small and difficult tasks in material handling is impressive. It is the future for the manufacturing sector. (P1)

We are looking for precision in our process, which will be get through the use of collaborative robots equipped with advanced sensors to enable the precise alignment and orientation of objects. [...] In the end, we will have a stable uniform pallet. (P3)

If we see bin-picking tasks and how collaborative robots will find out the correct parts from bins due to vision systems, to put it simply automation with collaborative robots would deal with even the most precise operations. (P5)

In our manufacturing process, cobot technology would be employed to palletize and depalletize products. We aim to implement this to lower the chance of errors in our processes. (P9)

The use of collaborative robots for **machine tending** was discussed by 8 participants. The participants talked about the integration of collaborative robots in the loading and unloading area (5 participants), and reducing setup times for machine tending operations (1 participant). A collaborative robot is seen as an innovative option to improve efficiency in operations. Some responses are:

Post-COVID-19 pandemic, most Australian manufacturing SMEs were impacted, particularly in the area of loading and unloading, often called machine tending. One innovative solution that is now being pursued is the integration of collaborative robots in this area. (P3)

Collaborative robots can exceed other technologies in reducing setup times for machine tending operations. In my assessment, this feature is a key point for decision makers when evaluating technology adoption options. (P6)

In terms of improving the efficiency of loading and unloading operations, cobots are the number one here. [...] Any manufacturing company should begin updating its process accordingly. (P10)

Others, however, thought that collaborative robots are not significant in machine tending due to their limitations in handling products of different weights and sizes.

Manufacturers can still benefit from using existing technologies. In my view, applying collaborative robots in machine tending aspect is not currently essential. (P4)

I see it as not important. Collaborative robots have limited load capacities and cannot manage different weights and sizes. Even with these limitations, manufacturers will likely use collaborative robots in machine-tending tasks. (P8)

The participants also discussed collaborative robot applications to enhance **quality inspection** in manufacturing (6 participants in total). Of these, 5 pointed to collaborative robots as an important advancement in quality inspection compared to manual inspection:

In Australia, SMEs have long relied on human inspection and some limited technologies. However, things change with the rise of a collaborative robot, as this technology can provide high inspection accuracy with repeatability and without concerns about fatigue or performance variation. (P2)

No doubt, collaborative robots are much better at quality inspection. For example, they can identify surface defects with good accuracy that are often missed during manual inspection. (P3)

It is a feasible technology, particularly when considering the use of AI-enabled collaborative robots or those equipped with optical sensors to ensure that every part meets exact guidelines. By doing so, most, if not all, manufacturing processes can benefit from enhanced overall quality. (P6)

However, one respondent, P10, expressed the view that collaborative robots are *"not in high demand"* for quality inspections in most small manufacturing industries.

The participants expressed positive opinions regarding cobots for the **welding** area. Of these, two referred to the advantages of cobots, for example, consistency, quality and safety in welding applications:

In the appliance industry, collaborative robots help to automate welding processes.

For example, in washing machine production, collaborative robots are programmed to deliver consistent welds according to strict quality standards. (P1)

Applying advanced tools, such as collaborative robots in welding, gives us excellent quality and safety in our metal products. (P10)

The remaining 2 participants, however, expressed more cautious perspectives:

P3 said that *"in Australia, there is no clear implementation for collaborative robot use in different welding environments"*. Likewise, P8 argued that *"dealing with cobots in welding is not fully defined"*

Finally, three participants discussed **material removal** the use of cobot applications. However, they noted future material removal applications rather than what is expected soon in SME manufacturing:

There are currently no examples of Australian SMEs implementing cobots in material removal applications. However, we hope to apply them in the near future to remove paint residue from the interior walls of our mixing areas. This is a very repetitive task, and by applying collaborative robots, we can save time and improve process efficiency. (P4)

It would be beneficial if we could take advantage of this technology in our industry. Collaborative robots could offer long-term solutions and improvements in material removal. However, the timeframe for widespread adoption in Australian manufacturing may extend over the next five years or longer. (P2)

We are hopeful about the changes that collaborative robots will bring in the future, both in material removal and broader manufacturing applications. (P6)

Two significant themes emerged from the participants' opinions promising cobot applications in the SME manufacturing sector.

Theme 1: Cobot technology remains an evolving and developing topic, as viewed by the managerial and technology experts in Australian manufacturing SMEs.

Of the ten participants, six expressed a thorough comprehension of the topic, whereas the other four acknowledged they had only a moderate level of knowledge. Some participants were not able to discuss cobot applications in Australian SMEs in detail. Most mentioned cobots as a new topic requiring further research and development, noting that there was little clarity on adopting and using them effectively.

Theme 2: The application of cobots in assembly processes within Australian manufacturing SMEs represents one of the most promising areas.

In this part, the interviewees were requested to name and evaluate the possible promising application areas of collaborative robots for Australian manufacturing SMEs. A summary of the interviewees' assessments is presented in Table 6.3. The data presented indicated that cobot applications in assembly were consistently identified by all participants as the main area of focus for manufacturing SMEs, receiving the highest frequency of mention. Cobot applications for material handling and machine tending were also commonly cited areas, although there was some variability in the opinions expressed by the participants about their feasibility and applicability. The remaining promising areas of cobot applications were either not widely considered and/or there was a lack of significant agreement about their uses or implementation.

Drawing on the themes explored, the decision was made to prioritise cobot applications in assembly processes.

6.3.2 Experts' Views on the Factors Influencing Collaborative Robot Adoption in Australian Manufacturing SMEs

Guided by the theoretical foundations of the thesis, participants were requested to share their views on the impact of various factors influencing cobot adoption by manufacturing SMEs in Australia. Furthermore, participants were requested to share any additional factors they deemed important in collaborative robot adoption. Consequently, six categories of factors were covered. For each category, the analysis process followed the methodology developed by [129], which involves the following steps: 1) data reduction was employed to transform raw data into a simplified dataset that can be managed; 2) pattern coding was used to identify themes or concepts; and 3) the main themes and codes developed during the pattern coding were summarised into a visual format, such as tables, to facilitate analysis and interpretation.

Table 6.3 : Summary of Participants' Assessments of Promising Collaborative Robot Applications for SME Manufacturing

Participant	**Assembly**	**Material Handling**	**Machine Tending**	**Quality Inspection**	**Welding**	**Material Removal**
P1	10	10	–	–	10	–
P2	10	–	10	10	–	10
P3	10	10	10	10	6	–
P4	10	8	6	10	–	10
P5	10	10	10	–	–	–
P6	10	10	10	10	–	5
P7	10	–	–	–	–	–
P8	10	8	6	–	6	–
P9	10	10	10	10	0	0
P10	10	10	10	6	10	0
Total	**10**	**8**	**8**	**6**	**4**	**3**

Note: "–" indicates that participants did not provide an assessment for the corresponding application.

For the first step in the content analysis, operational codes were created to determine constructs relevant to collaborative robot adoption. Further codes were created to assess the strength of factors with respect to collaborative robot adoption in manufacturing SMEs. The following four categories of codes were created for this purpose:

- Constructs were assigned strong effect values that were determined by the study participants such as " important," "very important," "extremely important," "most important," "quite important," "highly important," "strong," "essential," "imperative," "key," "crucial," "critical," "significant" and similar adjectives.
- Constructs were assigned moderate effect values that were determined by the study participants using terms such as "somewhat," "moderate," "some extent," "not the most important," and similar words.
- Constructs were assigned unclear effect values that were determined by the study participants using terms such as "maybe," "could be," "perhaps," "un-

clear," "seem to be possible" and similar words.

- Constructs for which the study participants explicitly rejected any influence were assigned no effect value.

Additionally, the analysis presents the mechanisms by which the interviewees assigned the aforementioned effect values.

Technological Context

The frequency of mentions and codes used in the analysis is presented in Table 6.4. Codes are arranged according to the strength of each factor. *The trialability* factor was the most mentioned by the study participants. In contrast, *relative advantage* was the most regularly discussed and received the highest rating. In general, all the theoretically established technological factors were not deemed weak or unrelated by the interviewees.

Table 6.4 : Coding Used to Analyse Technological Context

			Effect Strength			
Code	**Interpretation**	**Mentions**	**Strong**	**Moderate**	**No Effect**	**Unclear**
TECH-REA	Relative advantage	9	9	-	-	-
TECH-COMP	Compatibility	9	7	2	-	-
TECH-OBS	Observability	8	4	2	2	-
TECH-TRI	Trialability	10	4	4	1	1
TECH-COMX	Complexity	7	3	2	-	2

The results analysis revealed several themes related to the ***relative advantage*** effect on collaborative robot adoption by manufacturing SMEs. Six participants called it a "key technology" for SME manufacturing companies, while others considered it a "crucial" aspect of cobots. The relative advantage of cobots was discussed in terms of their ability to enhance productivity through collaborative teamwork between employees and machines and their cost-saving benefits for SMEs. In general, the participants expressed that there is a persistent need for continual updates with emerging technologies, such as collaborative robots, as they enhance safety without the need for cages which will add value to the company:

Relative advantage is a key factor, as productivity increases when collaborative robots are used in our company. Following the COVID-19 crisis, Australian firms experienced a significant labour shortage. At this stage, the use of collaborative robots allows the workforce and the cobot to operate together, enabling employees to focus on more complex and interesting tasks while the cobot performs repetitive, dirty, dull and dangerous activities. (P1)

When discussing the relative advantages of collaborative robots for small companies, cost savings can be achieved, particularly through reductions in setup time and maintenance requirements. (P7)

Ongoing updates are important to remain aligned with technological advancements, such as collaborative robots. A key advantage of cobots is their ability to work safely alongside employees. This feature enhances workplace safety without the need for protective cages and adds value to the company. (P9)

Four themes emerged during the data analysis process: 1) relative advantage is viewed as the strongest factor in the technological context for collaborative robot adoption; 2) the use of collaborative robots greatly enhances productivity; 3) collaborative robots provide cost-saving benefit for SMEs; and 4) cobots are able to operate safely in close proximity to workers, hence there is no need for safety cages or barriers to prevent accidents, which adds value to the company.

For the ***compatibility*** factor, 7 out of 10 participants emphasised the critical nature of compatibility as a factor, focusing on the matter of collaborative robots being compatible with all aspects of the manufacturing company, including its goals, vision, culture, or existing systems:

With regard to compatibility, collaborative robot technology aligns with our company's goals, vision, and expectations for using technology that meets our operational needs. (P2)

In my opinion, ensuring that collaborative robots are compatible with organisational values and culture is necessary. (P4)

Compatibility is essential, particularly in relation to collaborative robots' integration *with existing systems, whether hardware or software.* (P5)

For our company, this factor is critical; it is the basis for making investment decisions in new technology. (P6)

Two interviewees believed compatibility had a moderate impact because they definitely considered new technologies and their fit, and SMEs might take some time to integrate their systems with cobots:

Right, I can say that compatibility is a somewhat important factor. We definitely look at new technologies and how they can be implemented and adopted to fit the company into which they are being applied. (P9)

Ok, I think SMEs might take some time to integrate their devices or systems with collaborative robots, but it is not a highly critical factor that should be given significant consideration. (P10)

As a result, four themes emerged from the participants' discussions: 1) compatibility is taken into account in all aspects of the manufacturing company, including its goals, vision, culture, or existing systems (hardware or software). Hence, this factor is important in collaborative robot adoption; 2) compatibility is the basis for making investment decisions in new technology; 3) compatibility is important when considering new technologies and their fit for the company; 4) SMEs might take some time to integrate their systems with collaborative robots, but it is not a highly critical factor that should be given significant consideration.

Collaborative robot ***observability*** was discussed by 8 participants in the context of collaborative robot adoption by manufacturing SMEs. Differing opinions were expressed regarding the impact of observability. Some interviewees argued that observability was significant, particularly in light of the positive influence obtained in different applications of manufacturing and the success of companies in using this technology:

Indeed, observability is extremely important in the operations of SMEs. Assuming that it is possible to easily and efficiently observe the behaviour and performance of collaborative robots within the company environment, this would undoubtedly be a significant motivator for us to adopt and widely implement them in different applications. (P1)

Of course, as manufacturing companies, it is essential to keep up with new technologies, specifically those that facilitate operations, reduce the considerable time required for execution, lower costs, and so on. In this case, if we notice these benefits for our company, it will encourage us to adopt it on a wide scale. (P3)

Sure, the observability factor is quite important; we should observe if collaborative robots facilitate the work in our company, especially if we notice that companies from the same industry have used this technology and have had success. Our company will then decide to adopt it, whether in an assembly line or other applications. (P6)

Some participants mentioned that the observability factor somewhat impacts the adoption of collaborative robots:

From my perspective, seeing the benefits of collaborative robots doesn't necessarily mean we will immediately start adopting or implementing them. This depends on several factors, with observability not the most important factor in our decision-making process. (P2)

When we look at some manufacturing companies in the same industry that have adopted collaborative robots in their various applications and have seen the benefits of this technology, this doesn't necessarily mean that it will benefit us in the same way; we need to think about it. (P5)

The remaining two interviewees were unsure about the general impact of collaborative robots:

Yes, I believe that the observability factor could be important, meaning that if competitors have introduced this technology into their industries, it is possible for us to observe and consider it. However, it is not clear enough at this time whether we will adopt it, perhaps in the near future. (P7)

Let's look at adopting new technologies in the Australian manufacturing setting. There are certain procedures, measures, and policies that we need to consider carefully so this process may take a longer time. (P10)

Consequently, these themes emerged about the relationship between the adoption of collaborative robot and observability factor: 1) observability is a significant factor in collaborative robot adoption, though the strength of the impact is not clear; 2) observability is extremely important in the operations of SMEs, particularly if the benefits of collaborative robots can be observed in manufacturing applications; 3) this technology is likely to be adopted if other similar companies succeed in implementing it; 4) in light of the benefits of collaborative robots in different applications for companies, there may be some factors contributing to the decision-making process; 5) due to company procedures and policies, it may take a long time for companies to adopt new technologies.

Technology ***trialability*** was discussed by all participants in the setting of collaborative robot adoption by manufacturing SMEs. Most interviewees in this study agreed on the influence of trialability, however, to varying degrees. For those who assert it has an extreme impact, trialling new technologies on a small scale leads to the possibility of wide-scale implementation:

Definitely, for SMEs, the trialability factor is very important; the ability to try out new technology, such as collaborative robots, can reduce potential risks before making a substantial investment. (P2)

Sure, I believe that providing the opportunity to trial this new technology on a limited scale allows our company employees to understand the operational dynamics and how these can be more seamless; therefore, I rate this factor as highly important. (P6)

Right, I see trialability as essential when adopting any new technology; it should be tested on a small scale to assess its applicability and achieve the required benefits. This leads to the possibility of implementing it widely in the company. (P9)

Some participants also believed that this factor has a somewhat moderate impact on adoption rates in Australian SMEs and argued that new technologies could be trialled, and typically, company leaders make decisions on this quickly and within a set timeframe:

We initially trial and test our new technologies in our company and similar industries. Therefore, I do not think there are challenges in experimenting with any emerging technologies for our company. (P1)

We test and experiment with all technologies, and our manufacturing company leaders typically decide on experimentation quickly and within a set timeframe, so I give this factor medium to high importance. (P5)

I expect the trialability factor to affect, to some extent, the adoption rates in Aus-

tralian SMEs. (P6)

One participant indicated that this factor is unimportant and that collaborative robots can be integrated into SME operations without needing to be trialled:

No, this factor is not as important as I see it. In the case of SMEs, they can integrate collaborative robots into their operations more rapidly without the need for a trial, as progress here is clear and fast. (P8)

The subsequent themes emerged in the analysis process: 1) trialability plays a significant role in collaborative robot adoption, though it is unclear how strong the impact of this factor is; 2) SMEs can integrate collaborative robots into their operations without the need for trialling.

The final factor discussed by the participants was the ***complexity*** of collaborative robots. Differing views were expressed on the strength of the influence of complexity. Those who acknowledged the negative impact of this factor highlighted the high initial costs and the total costs that could increase with the need for ongoing support. In addition, they noted the need for diverse and costly training requirements, as well as the challenge of entirely using and understanding collaborative robots:

We must consider the high initial costs when considering the complexity factor and its significant negative impact on collaborative robots. Collaborative robots are characterised by very advanced features and capabilities, which make the initial cost high. As SMEs, we suffer from limited budget constraints. Additionally, the ongoing need for continuous support may further increase the overall cost of this type of robot. (P7)

Of course, collaborative robots require a high degree of collaboration between machines and operators in all factory applications. Hence, a high level of complexity will arise due to the need for diverse and costly training requirements, which will increase the time and cost for companies. Therefore, the subject needs to be studied extensively before adopting this type of technology. (P8)

To this point in time, I assume that complexity is a highly significant factor. Most Australian SMEs still struggle to understand and fully use collaborative robots. (P10)

Other participants also argued that the impact of complexity would be moderate because it takes time to correctly understand these emerging technologies and to consider safety features and regulatory compliance: *From my point of view, the complexity factor has a moderate impact. It doesn't pose a major challenge or barrier that could prevent the adoption of this technology. [...] It may take some time to understand it properly. This is quite natural when adopting emerging technologies.* (P2)

When considering the complexity factor, we must consider safety features and regulatory compliance and ensure sufficient support to deal with present or future issues. (P9)

Two of the participants, however, did not think that complexity posed a barrier to adoption. They argued that this type of robot is designed with a user-friendly interface and simplified programming because employees are highly trained and have an open mindset:

No, I don't think complexity is a barrier to adopting emerging technologies, especially collaborative robots. These robots are designed with user-friendly interfaces and simplified programming, which motivates SMEs to adopt this technology. (P1)

Overall, this factor is not important at all. In our company, we can adopt new technologies because we have highly trained employees, and they have an open mindset to experimenting with emerging technologies without imposing complexity or difficulty. (P5)

The analysis highlighted the subsequent key themes: 1) collaborative robots may be perceived negatively due to the high initial costs, costly training requirements, and the need to understand the technology, which may negatively impact its adoption; 2) this impact could be moderate because of the nature of technologies and considering safety features and regulatory compliance; 3) collaborative robots with user-friendly interfaces and trained employees decrease the effect of complexity.

The pattern codes and themes are presented in Table 6.5. As shown, all five factors proposed by [63] were maintained in the refined HCRAM conceptual model, even though the strength of the factors differ.

Table 6.5 : Interview Data Summary for the Technological Context

Pattern Codes	**Themes**	**Decision**
Relative Advantage → Collaborative Robot Adoption	-This is viewed as the strongest factor in the technological context for collaborative robot adoption; -provides high productivity; -cost-saving benefit for SMEs; -the advantage of collaborative robots is enhanced safety without the need for cages, which will add value to the company.	Retained in the technological context, with a strong relationship in technology adoption.

Table 6.5 (Continued)

Compatibility → Collaborative Robot Adoption	-compatibility is taken into account in all aspects of the manufacturing company, including its goals, vision, culture, or existing systems which makes it an important factor; -it is the basis for making investment decisions in new technology; -compatibility is important when considering new technologies and their fit for the company; -SMEs might take some time to integrate their systems with collaborative robots, but it is not a highly critical factor.	Retained in the technological context, with a strong relationship in technology adoption.

Table 6.5 (Continued)

Observability → Collaborative Robot Adoption	-unclear impact on the adoption process; -observability is extremely important in the operations of SMEs, particularly if the benefits of collaborative robots can be observed in manufacturing applications; - this technology is likely to be adopted if other similar companies succeed in implementing it; -considering the benefits of collaborative robots in different applications, some factors may affect decision-making process; -due to the implementation of certain procedures and policies, it may take a long time for companies to adopt new technologies.	Retained in the technological context, with a moderate relationship in the technology adoption.

Table 6.5 (Continued)

Trialability → Collaborative Robot Adoption	-perceived as having a moderate influence on adoption; -trialability is a significant factor in collaborative robot adoption, though it is unclear how strong of an impact this is; -SMEs can integrate collaborative robots into their operations without the need for trialling.	Retained in the technological context, with a moderate relationship in technology adoption.

Table 6.5 (Continued)

Complexity → Collaborative Robot Adoption	-collaborative robots may be perceived negatively due to the high initial costs, costly training requirements, and the need to understand the technology, which may negatively impact its adoption; -the negative impact of complexity could be moderate because of the nature of technologies and considering safety features and regulatory compliance; -collaborative robots with user-friendly interfaces and trained employees decrease the effect of complexity.	Retained in the technological context, with a negative relationship in technology adoption.

Organisational Context

Three organisational-related factors were discussed by the interviewees: top management support, organisational readiness, and workforce empowerment, the latter of which emerged as a new factor. The frequency of mentions and codes used in the analysis is presented in Table 6.6. Codes are arranged according to the strength of each factor. All three factors were viewed by the study interviewees as strongly influencing the adoption of cobots. Table 6.7 outlines all pattern coding and themes related to organisational factors in cobot adoption.

Table 6.6 : Coding Used to Analyse Organisational Context

			Effect Strength			
Code	**Interpretation**	**Mentions**	**Strong**	**Moderate**	**No Effect**	**Unclear**
ORGA-TMS	Top Management Support	10	9	1	-	-
ORGA-REA	Organisational Readiness	9	7	1	-	1
ORGA-WKEM	Workforce Empowerment	7	7	-	-	-

Top management support was close to being recognised by the interviewees as a strong determinant in collaborative robot adoption. It was perceived as important across all technologies. The interviewees used adjectives such as "crucial", "essential", and "important" when expressing their views on top management support. The majority discussed the importance of top management support in managing the risks associated with implementing emerging technology and ensuring successful technology adoption. Some responses in this regard included the following:

Our senior management is very supportive of emerging technologies. (P1)

...there are many challenges and big risks before moving forward with new technology implementation. How can we reduce this? So yes, top management is absolutely crucial in this. (P3)

Yes, adopting emerging technologies is a decision made by top leaders. (P4)

Full support from top/senior management is essential. This support ensures we can implement all new technologies without big issues. (P5)
I would say it is important; without their support, it would be impossible to adopt. If we talk about one of top management's key responsibilities, it is risk management; their approach greatly impacts technology adoption or acceptance. (P6)
Three themes emerged during the data analysis process: 1) this is viewed as the strongest factor in the organisational context for collaborative robot adoption; 2) it is viewed as commonly important across all technologies; 3) top management is also crucial in reducing the risks associated with adopting new technologies.
The second key factor influencing the adoption of cobots, based on the interviewees' insight, was ***organisational readiness***. The majority of participants talked about manufacturing readiness in relation to financial resources, human resources, and technology required for new technology adoption:
It is important for us to check if our organisation is ready, especially when it comes to having the right infrastructure and enough funds. (P3)
Besides top management support, we should always look at whether human resources, finances, and technological infrastructure requirements are sufficient to adopt new technologies. (P6)
For any manufacturing project, if the necessary resources are not available, it is hard to move forward. (P5)
We need to carefully see our readiness, like preparing our employees and securing long-term finances, before making decisions about adopting technologies. (P10)
A few participants also mentioned organisational readiness as an important factor, although small manufacturing industries often struggle with financial resources:
The organisational readiness factor is so important. As I see it, smaller Australian manufacturing firms face challenges with the initial investment needed. (P4)
We are interested in this. But, let me give you an example from our small industry. There is trouble related to the first costs and other resources as well. (P8)
Two themes emerged during the data analysis process: 1) manufacturing industries' readiness is an important factor which includes the technology required, financial resources, and the human resources for new technology adoption; 2) small manufac-

turing industries often struggle with financial resources.

Workforce empowerment emerged as a unique, strong factor within the organisational context of collaborative robot adoption, as discussed by 7 interviewees. They mentioned the importance of workforce empowerment by allowing them to have autonomous decision-making roles in industrial organisations:

Regarding the organisational aspect, you must look at how to empower your employees, as I believe this is crucial. You need to take the first step that involves them in the roles of decision making. (P3)

The topic of empowering the workforce through mentoring/ training etc. also comes up as manufacturers get ready to adopt collaborative robots. This empowerment is very very important. (P6)

If you look at cobots and their adoption, we notice we will be moving to modern transformation, new to humans and technology. We need to engage staff and give the workforce autonomy in decisions. More and more things or elements will change with the introduction of cobots, empowerment is one of the elements that will change humans' role inside manufacturing. (P5)

Looking ahead, as a part of our strategy in manufacturing, we are working to empower our employees by allowing them to share knowledge and decisions with each other. I am sure this will help us adopt new technologies more easily and reduce resistance. (P10)

Three themes emerged during the data analysis process: 1) workforce empowerment is perceived as a strong factor in collaborative robot adoption; 2) workforce empowerment occurs by allowing them to engage in autonomous decision making; 3) workforce empowerment occurs through training programs and mentoring.

The pattern codes and data analysis themes are provided in Table 6.7. Two factors proposed in the organisational context were maintained in the refined HCRAM conceptual model. A new factor emerged: workforce empowerment, which was included in the refined HCRAM conceptual model. The relationships between collaborative robot adoption and the three organisational factors were expected to be strong.

Table 6.7 : Interview Data Summary for the Organisational Context

Pattern Codes	**Themes**	**Decision**
Top Management Support → Collaborative Robot Adoption	-This is viewed as the strongest factor in the organisational context for collaborative robot adoption; -it is commonly important across all technologies; -it is also crucial in reducing the risks associated with adopting new technologies;	Retained in the organisational context, with a strong relationship in technology adoption.
Organisational Readiness → Collaborative Robot Adoption	-manufacturing industries' readiness is an important factor which includes the technology required, financial resources, human resources for new technology adoption; -small manufacturing industries often struggle with financial resources.	Retained in the organisational context, with a strong relationship in technology adoption.

Table 6.7 (Continued)

Workforce Empowerment → Collaborative Robot Adoption	-workforce empowerment is perceived as a strong factor in collaborative robot adoption; -workforce empowerment occurs by allowing them to engage in autonomous decision making; -workforce empowerment occurs through training programs and mentoring.	Included in the organisational context.

Environmental Context

The frequency of mentions and codes used in the analysis is presented in Table 6.8. Codes are arranged according to the strength of each factor. Government support was the most influential factor, despite some interviewees questioning its strength. The effect of competitive pressure was similarly ambiguous, with responses evenly divided between those who perceived an effect and those who did not. All pattern coding and themes related to environmental (external) factors in collaborative robot adoption are outlined in Table 6.9.

Table 6.8 : Coding Used to Analyse Environmental Context

			Effect Strength			
Code	**Interpretation**	**Mentions**	**Strong**	**Moderate**	**No Effect**	**Unclear**
ENVI-GOVS	Government Support	10	4	3	3	-
ENVI-COMPP	Competitive Pressure	8	3	2	3	-

The potential influence of the ***government support*** factor was mentioned by all study participants. Most discussed its positive impact, while opinions differ regarding the importance of its impact. Those who emphasised this factor argued that the government should primarily support development and research programs that encourage manufacturing SMEs to adopt cobots and enhance their global competitiveness.

The support from the government that we need here is not about subsidies or grants. Of course, that is important. But much more important is if the government supports development and research. The results will be great with the adoption of new technologies, like cobots. (P3)

Ok, support from the government is an essential thing. It is about helping with the necessary resources and guidance to help manage SMEs. By doing so, the government helps these companies to improve their operations, apply technologies, and compete globally. (P6)

I agree. We must consider government support for SMEs through research programs. Push adoption and implementation innovations by applying and supporting *these programs.* (P9)

Some participants argued that government support had a moderately important effect on adoption. They noted that manufacturing SMEs mostly rely on their internal resources:

I believe SMEs often rely on what they have from resources, I mean different types of resources. In fact, the question here is whether the support or assistance from the government meets what SMEs need or not or maybe it depends to some extent. (P5)

Governments need to offer support, but honestly, we have our resources and plans to adopt and to move to the next step without wasting time. (P10)

Some interviewees did not believe that government support has a significant influence on the adoption of cobots. They argued that government agencies are slow to adopt new technologies, and there is considerable red tape in accessing funding support:

The government takes a long time to adopt, and there are so many red tape challenges just to access any of the funding they make available to businesses like ours. We are not too encouraged by their support, so we prefer to rely on ourselves instead. (P1)

In our case, this type of support has not had much influence on our ability to adopt technologies. We hope the government steps up its support, whether through funding or more active campaigns. (P4)

Therefore, three themes emerged during the data analysis process: 1) government support is viewed as a positive factor, despite different opinions; 2) manufacturing SMEs mainly need support through development and research programs; 3) there are still considerable bureaucratic challenges in accessing funding support from the government.

There was disagreement in the opinions of study participants with regard to the extent to which ***competitive pressure*** influences the adoption of collaborative robots. Those who argued that competitive pressure point has a strong effect point to its role in driving SMEs to adopt and implement new technologies like collaborative robots:

Discussing the competitive pressure factor is extremely important, as it directly *pushes SMEs to apply the newest technologies.* (P1)

Some leading manufacturers in our sector are already using the latest process technologies. This put more pressure on us to compete and become one of the top SMEs in this field. (P6)

It is essential to have a competitive culture because it inspires us to adopt and implement services or technologies, like cobots. (P9)

Other interviewees acknowledged the moderate effect of competitive pressure, although they felt this pressure did not have a significant impact. They stated that such pressure can be helpful if it aligns with strategic goals, business requirements, and processes of manufacturing SMEs:

There are many reasons behind our decisions to adopt innovations/ technologies. When we see competitive pressure, this could boost SME industries to adopt, but it is important for us to check if it matches or supports the strategic goals of industry. I am with this factor but it is not very important. (P3)

Competitors, right they move us to look forward to adoption, but their impact is one part of the bigger picture. Decision makers should decide what competitors' pressure impacts an SME's business requirements and processes. This is one thing to ensure the right adoption. (P10)

Three interviewees did not think competitive pressure was an important factor in collaborative robot adoption. They argued that manufacturing SMEs prefer to maintain their stable state over risky competition and they have a successful business model:

Generally, this pressure is not something we worry about. Our decision makers are not rushing to adopt technologies just because of competitive pressure. (P2)

The competitive pressure factor, in my view, is not important at all. Our manufacturing business model is already successful on its own. (P4)

Many SME manufacturers prefer to remain stable over risky competition and do not give this factor priority in its adoption plan. (P8)

As a result, three themes emerged during the data analysis process: 1) competitive pressure can be a possible factor in a manufacturing SME's decision to adopt technology as a competitive point; 2) this pressure can be helpful if it aligns with strategic goals, business requirements, and the manufacturing processes of SMEs; 3) manufacturing SMEs prefer to maintain their stable state over risky competition, so competitive pressure is not seen as important.

The pattern codes and data analysis themes are provided in Table 6.9. Both factors proposed in the environmental (external) context were maintained in the refined HCRAM conceptual model. The relationships between the two factors (government support and competitive pressure) and the adoption of cobots were expected to be moderately positive.

Table 6.9 : Interview Data Summary for the Environmental Context

Pattern Codes	**Themes**	**Decision**
Government Support → Collaborative Robot Adoption	-This is viewed as a positive factor, despite different opinions; -manufacturing SMEs mainly need support through development and research programs; -there are still considerable bureaucratic challenges in accessing government funding.	Retained in the environmental context, with a moderate relationship in the technology adoption.

Table 6.9 (Continued)

Competitive Pressure → Collaborative Robot Adoption	-competitive pressure can be a possible factor in manufacturing SMEs deciding to adopt technology as a competitive point; -this pressure can be helpful if it aligns with strategic goals, business requirements, and the manufacturing processes of SMEs; -for those manufacturing SMEs which prefer to maintain their stable state over the risky competition, competitive pressure is not seen as important.	Retained in the environmental context, with a moderate relationship in technology adoption.

Human Context

Data codes and the frequency of mentions of human factors are presented in Table 6.10. Codes are arranged according to the strength of each factor. The innovativeness of decision-makers was the most significant factor and was discussed by all study interviewees. The presence of a project champion was seen as the second most influential factor. Conversely, prior experience was found to be relatively weak. Notably, during the interviews, one new factor emerged: employee capability, which was of particular interest. All pattern coding and themes related to human factors in collaborative robot adoption are outlined in Table 6.11.

All interviewees confirmed the strong influence of ***decision-maker innovativeness*** on collaborative robot adoption. They discussed the role of decision-makers innovativeness and connected it to openness to change as important characteristics of decision makers:

Table 6.10 : Coding Used to Analyse Human Context

			Effect Strength			
Code	**Interpretation**	**Mentions**	**Strong**	**Moderate**	**No Effect**	**Unclear**
HUM-INN	Decision-maker innovativeness	10	10	-	-	-
HUM-PROC	Project Champion	8	7	1	-	-
HUM-EMPC	Employee Capability	7	7	-	-	-
HUMA-PRIE	Prior Experience	6	1	-	3	2

Without a doubt, this is one of the most important human factors for adopting cobots. Specifically, for SMEs, decision-makers' innovativeness can enhance industrial performance and development. (P1)

Adopting novel technologies requires leaders with an innovative mindset and openness to change. We look to improve our manufacturing process, and our management is generally open to adopting technologies if they promise efficiency. (P3)

Yes, yes, talking about a collaborative robot and human side, on my side, I first see if decision makers have an innovative aspect that would lead the manufacturing company to embracing technological transformation. [...] It is very important to think *about that first.* (P9)

Some interviewees also pointed out that having innovative leaders is highly important to remain competitive in the market and to avoid falling behind:

This is what we need, and I will rate this factor as highly important in exploring and adopting collaborative robots. Companies without innovative leaders, literally in the next years, cannot survive big changes in industrial development in the dynamic market. (P6).

Of course, decision-making innovativeness has quite a big impact on decision adoption and prevents companies from falling behind in the technology race. (P8)

Three themes emerged during the data analysis process: 1) decision-makers' innovativeness can enhance SMEs' industrial performance; 2) an innovative mindset and openness to change are seen as the required characteristics for leaders when adopting novel technologies; 3) innovative leaders are highly important for remaining competitive in the dynamic market and avoiding falling behind in the technology race.

Seven interviewees agreed on the impact of the ***project champion's*** role in the adoption process. They spoke about the important role of driving unique ideas and possessing personal traits such as persuading and effectively communicating with all levels of manufacturers to create a supportive environment and successful adoption:

Do you know what drives outstanding ideas for manufacturing projects? The project champion. (P2)

Yes, also here, we are looking for the personal attributes of employees who can convince and communicate effectively with all levels of the manufacturing company. That is, not anyone can work on it, but a project champion with these attributes can drive the company to successful adoption. (P3)

True, one of the important human factors is the project champion and their excellent roles in our company. Look at their super role in encouraging a supportive environment for advanced projects and implementing advanced technologies like collaborative robots. (P6)

The project champion factor is very important when talking about their skills in persuasion and other soft skills that benefit manufacturing SMEs' projects and support their initiatives. I hope every Australian SME has at least one project champion.

(P10)

One study participant was less particular regarding the role of the project champion, mentioning that even without the project champion factor, manufacturing SMEs can still adopt collaborative robots if they have clear plans and project goals:

It is a good factor, but some SME manufacturers may not have employees working as project champions. You have to see if a manufacturer has clear plans/projects for adopting collaborative robots that may tackle the lack of project champions. (P8)

Three themes emerged during the data analysis process: 1) the project champion plays an important role in driving unique ideas; 2) the project champion possesses personal traits such as persuasion and an ability to communicate with all levels of a manufacturing SME to create a supportive environment leading to successful adoption; 3) manufacturing SMEs without project champions can still adopt collaborative robots if they have clear plans and project goals.

Employee capability emerged as one of the interesting strong human factors for collaborative robot adoption, as mentioned by 7 interviewees. They acknowledged the importance of investing in employees, developing their capabilities for the long term, and evaluating the current ones through new programs and initiatives:

I give you one comment here: when industrial companies plan to invest in their employees, they need to focus not just on preparing them for the short term; that is an issue we note, unfortunately! In short, with the new type of robot, cobot, it is time to prepare your employees with the important capabilities for the long term. (P1)

Yeah, about human factors, what about supporting new programs and initiatives for SME employees to qualify them to work with collaborative robots? That is totally what we will focus on to develop their capabilities and evaluate the existing ones. (P3)

Something we should think about is the abilities of the workforce or, in general, the human aspect of your manufacturing company. I believe that most Australian SMEs need a highly skilled workforce to implement advanced robots. (P6)

The whole working style will change when adopting collaborative robots; therefore, executing a high level of collaboration between manufacturing employees and cobots is not easy. Are employees ready? Are they ready based on their capabilities/possibilities?

One hundred percent? (P10)

Two themes emerged during the data analysis process: 1) employee capability is seen as an essential human aspect for long-term development when adopting collaborative robots; 2) there is a need to evaluate the current capabilities of employees and ensure they have a high level of skills through new programs and initiatives.

Contrary to expectations, ***prior experience*** was considered an insignificant or weak factor by three study participants. They argued that prior/previous experience will not be important in the adoption of collaborative robots if manufacturing organisations invest in preparing and qualifying their employees:

It doesn't matter if your employees have previous expertise or knowledge or not. This is not a big deal; seriously, what should your company do? Yes, invest in employees; invest in humans through high-level programs and training to be capable of working with collaborative robots. (P1)

Prior experience is not seen as an important factor. As I told you, for human factors, I can say that the massive benefit will be with leaders with an innovative mindset, as well as project or process champions who assist in adopting advanced robots: cobots. Yeah, like this, that's what I see up to now. (P3)

For some technology adoption, the prior experience factor acts as a condition for adoption. However, I think this factor is not essential in cobot adoption/ acceptance technology. Therefore, ignore employees' experience and look after developing employees' skills. Are there available development programs that support them in adopting and implementing cobots much more easily? (P6)

Two participants expressed that prior experience could potentially be a factor when adopting collaborative robots, but most SMEs ignored this factor:

Technology, like collaborative robots, needs a different approach compared to other new technologies. In this regard, the previous experience factor may be seen as a good aspect of adoption. But I am not confident in this. (P9)

It is a possible factor when adopting collaborative robots or similar technologies, but not a necessary factor as you think. [...] Yes, I am with some who said it is important, but not more or less. Most Australian manufacturing SMEs basically disregard it. (P10)

One participant still regarded it as a strong factor, mentioning employees' experiences can address technical issues during the adoption/implementation process:
What happens during the adoption/implementation of new technologies, for example, cobots, where many issues or technical issues will occur; that is normal. Some factors, of course, like an employee's background or experience with technologies address these issues to an acceptable level. (P4).
Three themes emerged during the data analysis process: 1) prior experience is considered an insignificant or weak factor; 2) SMEs should concentrate on investing in employees through advanced development programs instead of their prior experience or background; 3) only one positive view was expressed: employees' experiences can address technical issues during the adoption/implementation process.
The pattern codes and data analysis themes are provided in Table 6.11. For the refined HCRAM conceptual model, two original factors were retained, one original factor was removed, and one new factor was included. The decisions about the factors were made based on the frequency of mentions of each factor, the depth of participants' opinions, and the specific influence of the factor on improving model strength.

Table 6.11 : Interview Data Summary for the Human Context

Pattern Codes	**Themes**	**Decision**
Innovativeness $\rightarrow$ Collaborative Robot Adoption	-decision-makers' innovativeness can enhance SMEs' industrial performance; -an innovative mindset and openness to change are seen as the required characteristics for leaders when adopting novel technologies; -innovative leaders are very important to remain competitive in a dynamic market and to avoid falling behind in the technology race.	Retained in the human context, with a strong relationship in technology adoption.

Table 6.11 (Continued)

Project Champion → Collaborative Robot Adoption	-the project champion plays an important role in driving unique ideas; -the project champion possesses personal traits such as persuasion and an ability to communicate with all levels of the manufacturing industry to create a supportive environment and facilitate successful adoption; -manufacturing SMEs without project champions can still adopt collaborative robots if they have clear plans and project goals.	Retained in the human context, with a strong relationship in technology adoption.

Table 6.11 (Continued)

Employee Capability → Collaborative Robot Adoption	-employee capability is seen as an essential human aspect for long-term development when adopting collaborative robots; -there is a need to evaluate the current capabilities of employees and ensure they have a high level of skills through new programs and initiatives.	Included in the human context.

Table 6.11 (Continued)

Prior Experience → Collaborative Robot Adoption	-prior experience is considered an insignificant or weak factor; -SMEs should concentrate on investing in employees through advanced development programs instead of prior experience; -only one positive view was expressed: employees' experience can be useful in addressing technical issues during the adoption/implementation process.	Excluded from the human context.

Adoption Barriers

The study participants identified several barriers to the adoption of collaborative robots in manufacturing SMEs. Data codes and the frequency of mentions of barriers are listed in Table 6.12. Codes are arranged according to the highest number of mentions first. As seen, the first barrier was modified to a lack of technological knowledge instead of its original name, lack of knowledge. Based on the participants' perspectives, a new barrier to be added was regulatory uncertainty. However, the data provided about the safety factor lacked sufficient detail and depth. The fear of job loss factor was mentioned by only a few participants and was found to contrast with above mentioned inorganisation factor. As a result, in the finalised HCRAM conceptual model, two barriers were ultimately preserved. The outcomes of the pattern coding and the theme related to the barriers to cobot adoption are summarised in Table 6.13.

Table 6.12 : Coding Used to Analyse Adoption Barriers

			Effect Strength		
Code	Interpretation	Mentions	Strong	Moderate	Unclear
B-LKTN	Lack of Technological Knowledge	9	7	-	2
B-REGU	Regulatory Uncertainty	7	5	2	-
B-SAFI	Safety Issues	6	-	1	5
B-FJL	Fear of Job Loss	4	3	-	1

The most common obstacle to the adoption of collaborative robots was identified as ***a Lack of technological knowledge*** as mentioned by nine respondents. They argued that the issue extended beyond a general knowledge gap to a specific deficiency in technological skills among employees within the organisation. Consequently, this adoption barrier was defined as a lack of technological knowledge. The consensus was that this challenge could hinder cobot technology adoption in most SMEs, despite its benefits and applicability. This suggests that cobot technology remains relatively new, particularly in Australia:

I want to comment a little bit here, as I thought complexity was not a barrier to the *adoption of collaborative robots but actually when I see that overall most Australian SMEs are unwilling to go one step to prepare their workforce with new technology skills and knowledge. OK, it seems we can easily adopt collaborative robots as they have user-friendly interfaces but I see again most SMEs are limited by their technological and skill knowledge.* (P1)

Exactly, despite the advantages, this gap in technological understanding is a real barrier. (P3)

Not having enough technological knowledge is the biggest barrier. (P4)

I will be honest: the lack of technological knowledge comes from first decision makers who have not worked with new technology and do not see a need to change. That is why, yeah, this factor prevents adoption.(P6)

It is a challenge for SMEs. This technology is still emerging and is not widely used in Australia yet. (P10)

Two themes emerged during the data analysis process: 1) a lack of technological knowledge commonly inhibits technology adoption; 2) in most SMEs, collaborative robots are currently a technology that is not well understood and their use is limited. Interestingly, ***regulatory uncertainty*** related to collaborative robots emerged as a relatively novel concern, mentioned by only 6 respondents. They acknowledged that this factor could inhibit the adoption process for most Australian SMEs. They based their perception on the lack of clear regulations and existing regulations may not be suitable for innovations, such as collaborative robots:

Also, I see not all but most Australian SMEs have something like a long-term roadmap or sustainable roadmap with cobot adoption. Why? The simple answer is that there is no clear, future regulations/rules. That is too hard, I see it as one of barriers. (P1)

Keep in mind most barriers come from something outside of technology, for example, ambiguous laws and conditions. There are more details about that so it is complex - something which we usually suffer from. (P5)

The issue now with regulatory programs as far as I know, is that they have not been developed for new innovations: cobot, blockchain etc. I have seen some rules for these but I cannot confirm that. (P9)

Three themes emerged during the data analysis process: 1) regulatory uncertainty is perceived as a barrier for most manufacturing SMEs; 2) due to a lack of clear regulations, there is an absence of a sustainable roadmap with most manufacturing SMEs about collaborative robot adoption; 3) existing regulations may not be suitable for new technologies, such as collaborative robots. Importantly, unlike safety issues, the regulatory uncertainty includes broader governance and policy frameworks for technology adoption

Unlike the studies discussed that clearly determined the safety factor and its influence, ***safety issues*** was only somewhat agreed by one interviewee, who pointed to collaborative robot is still an emergent technology, particularly in Australian SME, and therefore, may need a proactive management approach to mitigate these concerns. The other five interviewees did not discuss this factor in-depth and clearly, and failed to evaluate its impact:

I do not expect safety to be a major problem; even so, it is different for every manufacturer. A lot of concerns could be handled by proactive management. (P2)

Not sure, really, safety perceptions need more and more time to assess. (P4)

I am undecided about safety. (P5)

The safety topic is new. It is too early to say our answer about whether it is a barrier or an enabler. (P9)

Two themes emerged during the data analysis process: 1) safety issues differ by manufacturer and can often be managed proactively; 2) however, it is unclear to what extent these concerns may inhibit collaborative robot adoption. Due to the lack of details and rich data about this barrier, and most participants did not identify its strength, it was excluded from the refined HCRAM conceptual model.

Fewer study participants indicated that ***fear of job loss*** was a potential barrier to collaborative robot adoption. However, this barrier was no different from other factors mentioned in the organisational context. Particularly, this factor was reverse of the aspects of empowerment and readiness:

I believe if decision makers are ready to empower or involve their employees in decsion make roles, this worry or resistance definitely reduces. (P3)

I have already talked about the availability of resources to go forward with the adop-

tion plan. It is very, very important to make sure that your employees are ready for this change; otherwise, an insecure job may negatively affect your adoption plan. (P5)

Anyway, it is a possible barrier. But what about a manufacturer's plan for their workforce? Training/involvement is the main element to have an industrial organisation without workforce fear or something like that. (P6)

Since only four study participants mentioned fear of job loss and no distinctive aspects of this barrier emerged beyond the organisational needs already outlined, it was excluded from the refined HCRAM conceptual model.

Table 6.13 presents the pattern codes and data analysis themes. In developing the refined HCRAM model, one original factor was retained, two original factors were excluded, and one new factor was introduced. Hence, two factors were included in the refined HCRAM conceptual model. Decisions regarding these factors were based on the frequency with which each factor was mentioned and the depth of participants' insights.

Table 6.13 : Interview Data Summary for Adoption Barriers

Pattern Codes	**Themes**	**Decision**
B-LKTN $\rightarrow$ Collaborative Robot Adoption	-This commonly inhibits technology adoption; -in most SMEs, collaborative robots are currently a technology that is not well understood and they are limited in their use.	Included in the adoption barriers.

Table 6.13 (Continued)

B-REGU → Collaborative Robot Adoption	-regulatory uncertainty is perceived as a barrier for most manufacturing SMEs; -due to a lack of clear regulations, there is an absence of a sustainable roadmap with most manufacturing SMEs on collaborative robot adoption; -existing regulations may not be suitable for new technologies, such as collaborative robots.	Included in the adoption barriers.
B-SAFI → Collaborative Robot Adoption	-safety differ by manufacturer and can often be managed proactively; -however, it is unclear to what extent these concerns may inhibit collaborative robot adoption.	Excluded from the adoption barriers.

Table 6.13 (Continued)

B-FJL $\rightarrow$ Collaborative Robot Adoption	-It needs to empower employees and involve them in the adoption process of technology, as fear of job loss will be reduced; -ensure that manufacturing employees are prepared for change; otherwise, negative emotions such as fear will affect the adoption plan.	Excluded from the adoption barriers.

6.4 Refined HCRAM Conceptual Model

Based on the qualitative data, amendments were made to the original HCRAM conceptual model to incorporate the perceptions and suggestions of decision-makers in Australian manufacturing SMEs. In summary, the following modifications were applied:

1. One new factor, namely empowerment, was added to the organisational factors dimension, as it was considered substantial in collaborative robot adoption by the participants.

2. One factor from the human factors dimension, namely prior experience, was eliminated, and one new factor, employee capability was added based on the interviewees' perceptions.

3. One adoption barrier name was changed to lack of technological knowledge instead of its original name, lack of knowledge. The safety issues and fear of job loss barriers were eliminated, and one new adoption barrier, regulatory uncertainty, was added based on the participants' perceptions.

The refined HCRAM conceptual model, which provided the foundation for the next phase of quantitative analysis, is shown in Figure 6.1. This model comprises five contexts: technology, organisational, environmental, human, and adoption barriers. The effects of fifteen factors across these contexts on collaborative robot adoption in Australian manufacturing SMEs will be analysed through a quantitative research survey.

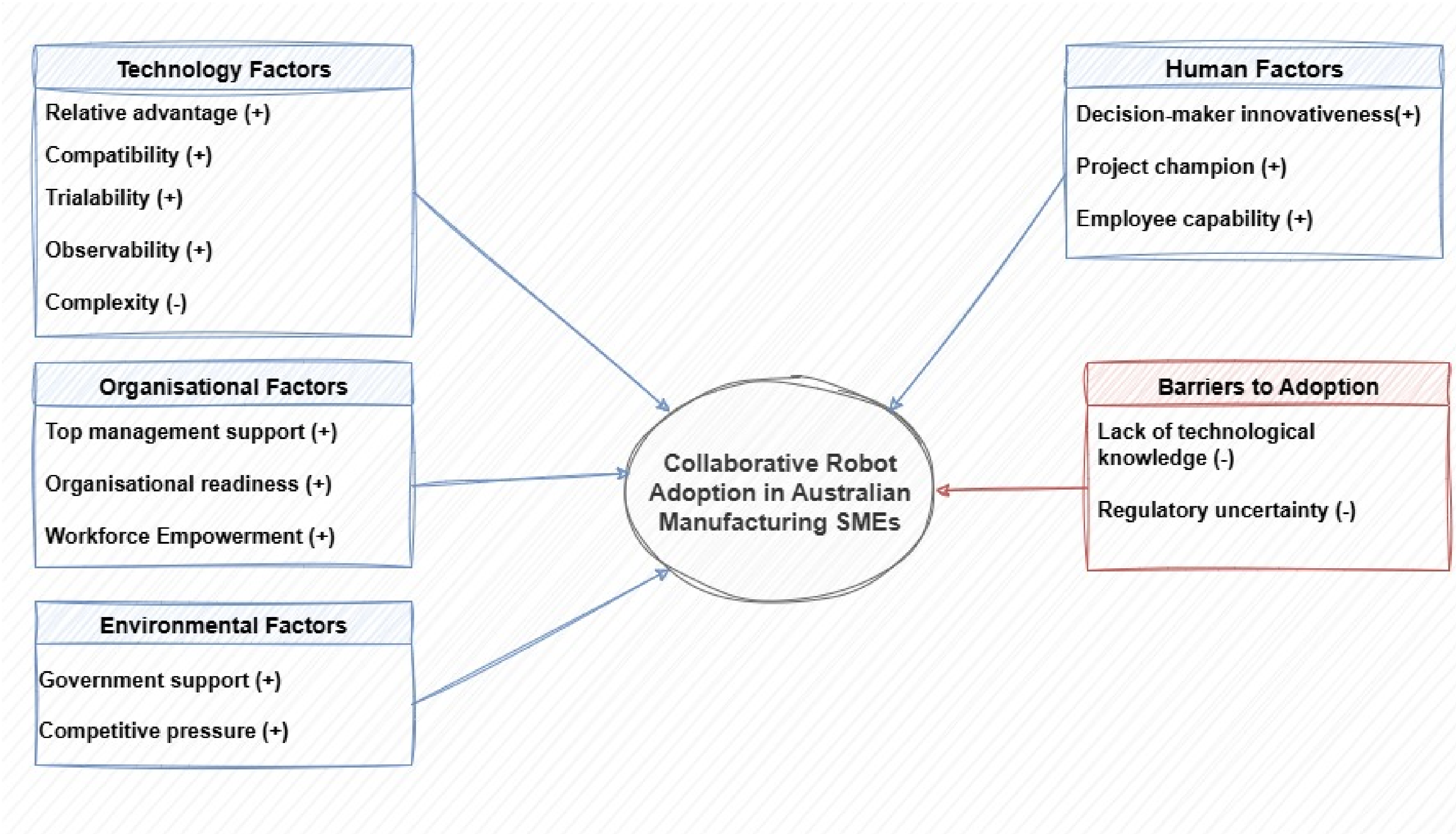


Figure 6.1 : Refined HCRAM Conceptual Model

6.5 Summary

Phase 1 presents detailed results from interviews with ten decision-making experts in managerial and technology specialist positions in Australian manufacturing SMEs. The interviewees shared their views on the current status of collaborative robot adoption in manufacturing SMEs and identified the factors they perceived as the most influential. The data interviews were analysed utilising a methodology in [129], which involves data reduction and simplification, pattern coding and concludes with data interpretation. The participants generally perceived collaborative robot applications in manufacturing SMEs as positive, even though they are not currently used extensively. Assembly emerged as the main area where cobots are applied. Consequently, the finalised questionnaire for the thesis was specifically tailored to focus on this application.

The next part of the analysis involves refining the framework, in which the interviewees discussed the existing factors and expressed their views on some additional factors they deemed important in the study. Three original factors were eliminated: prior experience, safety issues and fear of job loss. Three new propositional factors were added: workforce empowerment, employee capability and regulatory uncertainty. The refined HCRAM conceptual model comprises fifteen factors. The next chapter provides details of the survey results, which are based on the refined HCRAM conceptual model.

Chapter 7

Phase 2: Quantitative Research

7.1 Overview

Chapter 7 details the analysis of the data gathered through the survey instrument. It starts by describing the final study questionnaire, which includes the final study factors and measurement items (see Section 7.2). This chapter then describes the survey, including the response rate and summarises the participants' characteristics (see Section 7.3). It explains the preparation of the data for analysis, including data screening, to identify possible challenges with missing data, outliers, and bias that may be found during data collection (see Section 7.4). It also offers results related to the reliability of internal consistency and validity (see Section 7.5). It analyses the research structural model to verify the study hypotheses for each dimension: technology, organisation, environment, human, and adoption barriers (see Section 7.6). Finally, it summarises the results of this chapter (see Section 7.7).

7.2 Final Questionnaire

The research questionnaire was developed based on the refined HCRAM conceptual model presented in Section 6.4. To develop items for this study, previously established DOI, TOE and human dimension questionnaires were used as the foundation. Given the limited research on collaborative robot (cobot) adoption in manufacturing SMEs, this study consulted the established body of literature on the adoption of various technologies, such as intelligent robots, industrial IoT, etc., across the manufacturing industry and other sectors. Table 7.1 details the items and their references for the study variables. Appendix D presents the final questionnaire.

This instrument was organised into several sections:

- *Section 1:* This section provides the cover letter, which contains the consent

Table 7.1 : Summary of Item Development and Empirical References

Variables	Items	References
Technological Context		
Relative advantage	5	[54],[56],[134]
Compatibility	4	[54],[56],[134]
Trialability	4	[54],[134],[170],[171],[172]
Observability	5	[54],[170],[171],[172]
Complexity	4	[54],[56],[170],[173]
Organisational Context		
Top management support	5	[54],[56],[171],[173],[174],[175]
Organisational readiness	5	[54],[59],[176]
Workforce Empowerment	3	[177]
Environmental Context		
Government support	4	[94],[178]
Competitive pressure	4	[54],[56],[59],[174],[178]
Human Context		
decision-maker Innovativeness	3	[179],[180]
Project champion	3	[181]
Employee capability	3	[182]
Adoption Barriers		
Lack of technological knowledge	3	[183]
Regulatory uncertainty	2	[183]
Adoption		
Collaborative robot adoption intent	4	[54],[170],[184] originally from [56],[185],[186],[187] and [188]

page for the researcher questionnaire. It provides information about the researcher and her supervisor's contact details, the research, and the university's ethics and policy.

- *Section 2:* This section provides a brief description of cobot technology, particularly in the assembly process, to help decision-makers with limited knowledge of cobots understand the technology before responding to the questions. It also collects general information about the participants and manufacturing organisations, such as educational level, job position, manufacturing organisation location, manufacturing organisation size (employee number), and knowledge level of cobots. It is noted that a screen question will be applied to the location question to ensure that only participants from manufacturing SMEs are eligible to respond. Thus, responses from manufacturing organisations that do not meet this criterion (i.e., micro < 5 employees or large with 200 or more) will be excluded and will not be permitted to complete the questionnaire.

- *Section 3:* This section covers the cobot adoption factors (technological, organisational, environmental, human and adoption barriers) and cobot adoption intent. In addition, the questionnaire includes an open-ended question to gather additional comments, encouraging participants to offer suggestions to enhance the research.

7.3 Descriptive Analysis

The study obtained 734 responses from the target population. Several exclusion criteria were utilised to verify the quality of the data collected:

1. Incomplete surveys were excluded;

2. Surveys completed in less than the minimum (6 minutes, determined during the pilot test as necessary to read and respond to the questions appropriately) were excluded;

3. Surveys in which all items were answered with identical responses (including reverse-score questions to assess whether respondents were reading and

responding thoughtfully) were excluded.

Following the application of the exclusion criteria, 640 valid questionnaires remained for the final analysis. This number exceeds the recommended minimum threshold of 610 discussed in 4.6, thereby ensuring a sufficient sample size, which improves the reliability and rigour of the results. The achieved response rate was (64%), which is in line with the previously cited organisational research average of (68%) [189]. The demographic statistics of the respondents, including their job role, highest degree qualification, and organisational characteristics, such as the location and size of the manufacturing organisation, are presented in Table 7.2. It also includes information on the participants' familiarity with cobots.

7.3.1 Educational Level

Table 7.2 shows a high percentage of respondents (59.53%) possessed a bachelor's degree and (24.38%) held a postgraduate degree. (12.81%) of respondents held a diploma and only one (3.28%) had a high school qualification as their highest educational level.

7.3.2 Job Position

The majority (63.13%) of respondents were in middle management, holding roles such as plant managers, production managers, etc., followed by those who were from top management, such as the president, CEO, director, etc.(20.78%) and Technology specialists, such as IT manager and engineers (16.09%).

7.3.3 Organisation Location

Table 7.2 indicates that most of the respondents were from two states: NSW (45.31%), followed by VIC (20.63%). A small proportion of respondents were from other states and territories: specifically SA (5.78%), WA (3.44%), and NT (3.28%). The remaining respondents were from the ACT (0.47%).

Table 7.2 : Sample Characteristics

Characteristic		**No.**	**%**
Educational Level	High school	21	3.28
	Diploma	82	12.81
	Bachelor degree	381	59.53
	Postgraduate degree	156	24.38
Job Position	Top Management	133	20.78
	Middle Management	404	63.13
	Technology Specialists	103	16.09
	Other	0	0.0
Organisation Location	Australian Capital Territory (ACT)	3	0.47
	New South Wales (NSW)	290	45.31
	Victoria (VIC)	132	20.63
	Queensland (QLD)	127	19.84
	Western Australia (WA)	22	3.44
	South Australia (SA)	37	5.78
	Northern Territory (NT)	21	3.28
	Tasmania (TAS)	8	1.25
Organisation Size	5 -19 employees	205	32.03
	20 -199 employees	435	67.97
Knowledge of Collaborative Robots	Good knowledge	343	53.59
	Some knowledge	297	46.41

7.3.4 Organisation Size

Table 7.2 shows that more than half (67.97%) of the participants were from medium-sized manufacturing organisations (20-199 employees), while the remaining (32.03%) were from small-sized manufacturing organisations (5-19 employees).

7.3.5 Knowledge of Collaborative Robots

In terms of familiarity with cobot technology, 343 respondents (53.59%) had good knowledge and 297 respondents (46.41%) had some knowledge. The results present the overall awareness of technology among the respondents.

7.4 Data Preparation for Analysis

7.4.1 Data Screening

Data screening is essential to ensure data integrity before applying inferential statistical tests. This step included several screening processes: checking for missing values, data normality, outliers and non-response bias tests. These processes are clarified in the following.

Nonresponse Bias

Nonresponse bias occurs in survey research when some respondents of the selected sample are unwilling or unable to participate in the survey [190]. This can result in systematic differences between nonrespondents and those who completed the survey, potentially limiting the representativeness of the results. According to [151], late and partial respondents can serve as proxy indicators for nonrespondents and may be compared with early respondents to detect bias. In this study, a series of t-tests was conducted to compare the responses of thirty early respondents with those of thirty late respondents. The analysis aimed to identify any significant differences in responses to the scale item. The results revealed no statistically significant differences between early and late respondents, suggesting that the dataset is free from nonresponse bias.

Missing Data

The next process included screening for missing data and reporting means and standard deviations. Appendix E presents the descriptive statistics for data. A total of 640 valid questionnaires were collected, each containing complete responses for all 61 items, indicating there were no missing values in the dataset. All items mean exceeded 3, that mean the midpoint of the 7 scale, confirming that participants generally rated all items positively. To assess the variability of the sample means for all survey items, the standard error of the mean was calculated [191]. Data values range between 0.0305 (3.05%) and 0.0574 (5.74%), indicating low variability in the sample mean.

Normality

It refers to gathered data that follows a bell-shaped distribution pattern [148],[192]. The extreme non-normal distribution can be problematic in assessing the significance of the parameters [193]. To verify the normality of the collected data, kurtosis and skewness tests were performed. For a normal univariate distribution, some researchers propose that the skewness and kurtosis values should be within ± 2 [194]. Others suggest looser values for kurtosis assessment at ± 7 [148],[195]. However, due to the robustness of SEM tests, some argue that the data distribution should be deemed normal if kurtosis values fall within (± 10) and skewness values fall within (± 3) [152],[196].

In this research, normality measures applied to the scale items are presented in Appendix F. The results indicated kurtosis values ranging from -1.046 to 1.591 and skewness values ranging from -1.072 to 0.520. These values fall within or close to the stringent range recommended in the literature, confirming that the data can be considered normally distributed for the purposes of this study.

Outliers

Outliers are observations that deviate from the mean values [197]. They can influence model fit, parameter estimation and standard errors. In large samples, a small percentage of unusual responses is expected and may occur naturally. The z-scores were successfully used to screen outliers in the dataset, where all items are converted into standardised values/z-scores. As stated by [198] and [199], a data value is deemed to be an outlier if its standardised score is above or below 3.29.

Accordingly, as shown in Appendix G, the results of the z-scores for the scale items indicate that some responses could be deemed outliers. Nevertheless, the total number of outlier responses across the five different items was 26: 7 (TF_RA_Q1), 3 (TF_RA_Q4), 2 (TF_OB_Q2), 5 (TF_OB_Q5) and 9 (HF_EC_Q1), representing only (4.06%) of the total observations. As stated by [199], deleting data outliers is advised only when there is significant evidence that these outliers fall outside what is usually noted in the dataset. Other authors also suggest that if the percentage of outliers does not exceed 5%, they may be retained rather than removed from the dataset [200]. In this dataset, the presence of 4.06% or fewer can be considered normal. Given that a 7 Likert scale was used, this can reasonable that a small number of respondents expressed very strong positive or negative views on certain items. Therefore, it was determined that retaining outliers in all survey responses would help preserve the integrity of the data.

7.5 Reliability and Validity of the Survey

Before evaluating the research structural model, two essential elements of data quality, namely reliability and validity, should be measured. Factor analysis is an important technique used to validate measurements, evaluate the performance of individual items and confirm the study constructs. In this study, two important methods are employed: confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) [152]. The CFA method is used to validate the proposed model by confirming it aligns with the research context, whereas the EFA method is employed to identify the data structure and the factors that explain the maximum variance [201],[202]. As a result, CFA is more appropriate for validating established measures and models, whereas EFA is better suited for the early phases of a study or for testing new instruments.

The model in this study includes items related to organisational, human and adoption barrier constructs that have not been previously examined in the same study context. Consequently, both EFA and CFA were applied. To improve the quality of factor analysis, several authors suggest using the EFA method to specify the model, followed by the CFA method to validate it [203],[204],[205]. This research follows these recommendations.

In the HCRAM conceptual model, factor analysis and reliability analysis were conducted for five multi-variable dimensions: technology factors (5 variables), organisational (3 variables), environmental (2 variables), human (3 variables), and adoption barriers (2 variables). The EFA stage commenced with extraction methods to evaluate item correlations, employing principal axis factoring in this study. Rotation techniques, including Promax rotation (an oblique method) [199]. were applied to enhance the interpretability of the factor structure. The Kaiser-Meyer-Olkin (KMO) measure was used to verify the appropriateness of the dataset for factor analysis, with a threshold of 0.7 or higher [152]. Cross-loadings and communality values were calculated for individual items to assess their acceptance in the final research model. For the commonality score, a value above 0.4 is deemed acceptable [206]. For cross-loadings, a common threshold for acceptability is ± 0.2, which means that items are loading onto more than one factor [207]. All items have to be equal to or greater than 0.5 on their respective factor, and the average of the loadings for all items associated with that factor has to be 0.7 or higher, according to [150] and [148]. After performing EFA, all constructs were assessed for internal consistency employing two measures: Cronbach's alpha, with an acceptable value of ≥ 0.7 [150], and composite reliability (CR), with a threshold of > 0.7 [148],[149].

A CFA was the final stage method performed to validate each dimension in the model. As recommended by [152], chi-square in research models exceeding 200 cases may be misleading. Then, the study determined the model fit with multiple indices such as (SRMR, ≤ 0.1), (RMSEA, ≤ 0.1), comparative fit index (CFI, ≥ 0.9), incremental fit index (IFI, ≥ 0.9) and Tucker-Lewis index (TLI, ≥ 0.9) [148],[152],[153]. Construct validity was tested through discriminant and convergent validity analyses [208]. The Average variance extracted (AVE) value of ≥ 0.5 indicates the presence of convergent validity, while discriminant validity is demonstrated when the square root of the AVE exceeds the cross-correlation of constructs, as recommended by

[148] and [149].

7.5.1 Reliability and Validity: Technology Dimension

This study analysed five factors within the technology dimension, namely relative advantage (RA), compatibility (COM), observability (OBS), trialability (TRI) and complexity (CPX). Table 7.3 presents the output of the EFA Pattern Matrix. The initial KMO value for the five constructs was 0.916, which exceeds the 0.7 threshold and a cumulative variance of 66.853%. All commonalities were above the threshold of 0.4. It was observed that eight items might be problematic: RA_1, COM_4, OBS_1, OBS_2 and OBS_5 did not clearly load with their corresponding factors, and their loadings were weak (0.489, 0.463, 0.481, 0.473, and 0.493, respectively). The other three items, RA_Q3, RA_Q4 and COM_Q3, indicated cross-loadings within the range of ±0.2, and their loadings were notably weak. Consequently, it was decided to remove all seven items to prevent problems with discriminant validity. After removing the seven items, the final EFA results showed no problems with weak loadings or factor loadings, with a KMO value of 0.869 and a cumulative variance of 81.273% (see Table 7.4).

Table 7.3 : Initial Pattern Matrix of EFA for Technology Factors

		Component				
Items	**Communality**	**1**	**2**	**3**	**4**	**5**
TF_RA_Q1	0.653				0.489	
TF_RA_Q2	0.700			0.884		
TF_RA_Q3	0.746			0.512	0.439	
TF_RA_Q4	0.750			0.578	0.498	
TF_RA_Q5	0.747			0.975		
TF_COM_Q1	0.662				0.705	
TF_COM_Q2	0.678				0.547	
TF_COM_Q3	0.563			0.442	0.520	
TF_COM_Q4	0.579			0.463		
TF_TRI_Q1	0.901	0.936				
TF_TRI_Q2	0.896	0.960				
TF_TRI_Q3	0.845	0.946				
TF_TRI_Q4	0.785	0.892				
TF_OBS_Q1	0.486				0.481	
TF_OBS_Q2	0.471				0.473	
TF_OBS_Q3	0.669					0.896
TF_OBS_Q4	0.751					0.917
TF_OBS_Q5	0.551					0.493
TF_CPX_Q1	0.820		0.858			
TF_CPX_Q2	0.808		0.870			
TF_CPX_Q3	0.726		0.762			
TF_CPX_Q4	0.678		0.759			
KMO=0.916, p<0.01						
Rotation converged in 5 iterations.						

Table 7.4 : Final Pattern Matrix of EFA for Technology Factors

		Component				
Items	**Communality**	**1**	**2**	**3**	**4**	**5**
TF_RA_Q2	0.783			0.833		
TF_RA_Q5	0.821			0.922		
TF_COM_Q1	0.829					0.884
TF_COM_Q2	0.821					0.849
TF_TRI_Q1	0.905	0.922				
TF_TRI_Q2	0.907	0.954				
TF_TRI_Q3	0.853	0.935				
TF_TRI_Q4	0.796	0.885				
TF_OBS_Q3	0.814				0.904	
TF_OBS_Q4	0.793				0.856	
TF_CPX_Q1	0.829		0.912			
TF_CPX_Q2	0.818		0.927			
TF_CPX_Q3	0.730		0.820			
TF_CPX_Q4	0.678		0.763			
KMO=0.869, p<0.01						
Rotation converged in 5 iterations.						

Internal consistency of the technology-related construct data was assessed using Cronbach's alpha and composite reliability following EFA, as shown in Table 7.5. The results indicate high reliability for all constructs; hence, all five were retained for CFA.

Table 7.5 : Reliability Test of Technology Constructs

Construct	**Items**	**Cronbach's alpha**	**CR**
RA	2	0.742	0.762
COM	2	0.774	0.780
TRI	4	0.944	0.948
OBS	2	0.716	0.731
CPX	4	0.887	0.879

CFA outcomes for all the retained constructs are provided in Table 7.6. The following indices (CFI= 0.967, IFI=0.967, TLI=0.955, RMSEA= 0.070, SRMR= 0.0551) indicate the model fit is acceptable. All coefficients of standardised regression weight (SRW) were above 0.6, generally showing strong loadings. The outcomes show that the AVE value exceeded 0.5, thus confirming convergent validity. The result also confirmed the discriminant validity by showing that $\sqrt{AVE} = 0.884$ was greater than the highest correlation (r = 0.652) between compatibility and observability.

Table 7.6 : CFA Outcomes for Technology Constructs

Items	**SRW**	**AVE**	$\sqrt{\textbf{AVE}}$	**Highest Construct Correlation**	**Model Fit**
TF_RA_Q2	0.890	0.782	0.884	0.652	CFI= 0.967 IFI= 0.967 TLI= 0.955 RMSEA= 0.070 SRMR = 0.0551
TF_RA_Q5	0.669				
TF_COM_Q1	0.775				
TF_COM_Q2	0.824				
TF_TRI_Q1	0.945				
TF_TRI_Q2	0.950				
TF_TRI_Q3	0.889				
TF_TRI_Q4	0.833				
TF_OBS_Q3	0.722				
TF_OBS_Q4	0.794				
TF_CPX_Q1	0.960				
TF_CPX_Q2	0.936				
TF_CPX_Q3	0.663				
TF_CPX_Q4	0.614				

7.5.2 Reliability and Validity: Organisational Dimension

In the organisational dimension of the study, three factors were identified: organisational readiness (OR), top management support (TMS), and Workforce empowerment (EMP). Table 7.7 provides the outcomes of the EFA Pattern Matrix. The initial KMO value for the three constructs was 0.927, which exceeds the 0.7 threshold and a cumulative variance of 70.495%. All commonalities were above the threshold of 0.4. It was observed that four items might be problematic: OF_TMS_Q4 and OF_TMS_Q5 did not clearly load with their corresponding factors and their loadings were weak (0.475 and 0.486, respectively). The other two items, OF_ORA_Q1 and OF_ORA_Q5, showed cross-loadings within the range of ±0.2. Therefore, it was decided to remove all four items to prevent problems with discriminant validity. After removing the four items, the final EFA results presented no problems with factor loadings, with a KMO value of 0.891 and a cumulative variance of 78.915%(see Table7.8).

Table 7.7 : Initial Pattern Matrix of EFA for Organisational Factors

		Component		
Items	**Communality**	**1**	**2**	**3**
OF_TMS_Q1	0.780		0.946	
OF_TMS_Q2	0.748		0.792	
OF_TMS_Q3	0.640		0.576	
OF_TMS_Q4	0.568	0.475		
OF_TMS_Q5	0.670	0.486		
OF_ORA_Q1	0.675		0.476	0.527
OF_ORA_Q2	0.767			0.865
OF_ORA_Q3	0.781			0.760
OF_ORA_Q4	0.768			0.672
OF_ORA_Q5	0.632		0.462	0.515
OF_EMP_Q1	0.681	0.531		
OF_EMP_Q2	0.776	0.829		
OF_EMP_Q3	0.679	0.761		

Note: KMO=0.927, p<0.01

Rotation converged in 7 iterations.

Table 7.8 : Final Pattern Matrix of EFA for Organisational Factors

		Component		
Items	**Communality**	**1**	**2**	**3**
OF_TMS_Q1	0.806	0.982		
OF_TMS_Q2	0.794	0.828		
OF_TMS_Q3	0.690	0.666		
OF_ORA_Q2	0.742		0.865	
OF_ORA_Q3	0.848		0.920	
OF_ORA_Q4	0.820		0.791	
OF_EMP_Q1	0.730			0.596
OF_EMP_Q2	0.847			0.875
OF_EMP_Q3	0.827			0.919
Note: KMO=0.891, p<0.01, Rotation converged in 5 iterations.				

After conducting EFA, the reliability of each organisational construct was measured to check the internal consistency of the retained data. Table 7.9 shows composite reliability and Cronbach's alpha analyses, implying high reliability for three constructs. Therefore, all three were retained for CFA tests.

Table 7.9 : Reliability Test of Organisational Constructs

Construct	**Items**	**Cronbach's alpha**	**CR**
TMS	3	0.838	0.816
ORA	3	0.858	0.881
EMP	3	0.852	0.835

CFA outcomes for all the retained constructs are shown in Table 7.10. The following indices (CFI= 0.987, IFI= 0.987, TLI= 0.972, RMSEA= 0.067, SRMR =

0.0295) indicate the model fit is acceptable. All coefficients of SRW were above 0.6, generally showing strong loadings. The results showed that the AVE value exceeded 0.5, thus confirming convergent validity. The result also confirmed the discriminant validity by showing that $\sqrt{AVE} = 0.834$ was greater than the highest correlation (r = 0.793) between organisational readiness and empowerment.

Table 7.10 : CFA Outcomes for Organisational Constructs

Items	**SRW**	**AVE**	**$\sqrt{\text{AVE}}$**	**Highest Construct Correlation**	**Model Fit**
OF_TMS_Q1	0.665	0.697	0.834	0.793	CFI= 0.987 IFI= 0.987 TLI= 0.972 RMSEA= 0.067 SRMR = 0.0295
OF_TMS_Q2	0.809				
OF_TMS_Q3	0.836				
OF_ORA_Q2	0.717				
OF_ORA_Q3	0.874				
OF_ORA_Q4	0.931				
OF_EMP_Q1	0.856				
OF_EMP_Q2	0.770				
OF_EMP_Q3	0.751				

7.5.3 Reliability and Validity: Environmental Dimension

This study analysed two factors within the environment dimension: government support (GS) and competitive pressure (CP). Table 7.11 illustrates the outcomes of the EFA Pattern Matrix. The KMO value for the three constructs was 0.842, which exceeded the threshold of 0.7 and a cumulative variance of 81.974%. It was observed that there were no issues with cross-loadings. Therefore, all data were retained for reliability analysis.

Table 7.11 : Pattern Matrix of EFA for Environmental Factors

		Component	
Items	**Communality**	**1**	**2**
GS_1	0.694		0.843
GS_2	0.813		0.908
GS_3	0.807		0.879
GS_4	0.740		0.857
CP_1	0.898	0.938	
CP_2	0.916	0.963	
CP_3	0.879	0.935	
CP_4	0.811	0.904	
KMO=0.842, p<0.01,			
Rotation converged in 3 iterations.			

The internal consistency of the data related to the environment-related construct was assessed after conducting EFA, as presented in Table 7.12. The results indicate high reliability across all constructs; hence, all five were retained for CFA.

Table 7.12 : Reliability Test of Environmental Constructs

Construct	**Items**	**Cronbach's alpha**	**CR**
GS	4	0.887	0.874
CP	4	0.945	0.953

CFA outcomes for all the retained constructs are presented in Table 7.13. The following indices (CFI= 0.992, IFI= 0.992, TLI= 0.986, RMSEA= 0.072, SRMR = 0.0119) indicate the model fit is acceptable. All coefficients of SRW were larger than 0.7, proving to be strong loadings. The results showed that the AVE value exceeded 0.5, thus confirming convergent validity. The results also confirmed the discriminant validity by showing that $\sqrt{AVE} = 0.903$ was greater than the highest correlation (r = 0.409).

Table 7.13 : CFA Outcomes for Environmental Constructs

Items	**SRW**	**AVE**	$\sqrt{\textbf{AVE}}$	**Construct Correlation**	**Model Fit**
EF_GS_Q1	0.830	0.817	0.903	0.407	CFI= 0.992 IFI= 0.992 TLI= 0.986 RMSEA= 0.072 SRMR = 0.0119
EF_GS_Q2	0.930				
EF_CP_Q1	0.934				
EF_CP_Q2	0.957				
EF_CP_Q3	0.917				
EF_CP_Q4	0.845				

7.5.4 Reliability and Validity: Human Dimension

Three factors were identified within the human dimension: decision-maker innovativeness (INN), project champion (PC) and employee capability (EC). Table 7.14 shows the outcomes of the EFA Pattern Matrix. The initial KMO value for the three constructs was 0.909, which exceeds the 0.7 threshold and a cumulative variance of 81.511%. All commonalities were above the threshold of 0.4. It was observed that one item might be problematic: HF_EC_Q1 did not clearly load with its corresponding factor, and the loading power was notably weak. Therefore, this item was excluded to prevent problems with discriminant validity. After removing it, the final EFA results presented no problems with factor loadings, with a KMO value of 0.894 and a cumulative variance of 84.626% (see Table 7.15).

Table 7.14 : Initial Pattern Matrix of EFA for Human Factors

		Component		
Items	**Communality**	**1**	**2**	**3**
HF_INN_Q1	0.714	0.603		
HF_INN_Q2	0.828	0.879		
HF_INN_Q3	0.793	0.906		
HF_PC_Q1	0.844		0.842	
HF_PC_Q2	0.903		0.916	
HF_PC_Q3	0.880		0.904	
HF_EC_Q1	0.683		0.447	
HF_EC_Q2	0.823			0.854
HF_EC_Q3	0.867			0.972

Note: KMO=0.909, p<0.01

Rotation converged in 6 iterations.

Table 7.15 : Final Pattern Matrix of EFA for Human Factors

		Component		
Items	**Communality**	**1**	**2**	**3**
HF_INN_Q1	0.732		0.645	
HF_INN_Q2	0.864		0.912	
HF_INN_Q3	0.845		0.946	
HF_PC_Q1	0.845	0.871		
HF_PC_Q2	0.903	0.926		
HF_PC_Q3	0.880	0.914		
HF_EC_Q2	0.842			0.877
HF_EC_Q3	0.85			0.954

Note: KMO=0.894, p<0.01

Rotation converged in 5 iterations.

The internal consistency of the retained data related to the human-related construct was assessed using Cronbach's alpha and composite reliability following EFA, as outlined in Table 7.16. The results indicate high reliability for all constructs; hence, all five were retained for CFA.

Table 7.16 : Reliability Test of Human Constructs

Construct	**Items**	**Cronbach's alpha**	**CR**
INN	3	0.869	0.876
PC	3	0.926	0.930
EC	2	0.836	0.839

The CFA outcomes for all the retained constructs are shown in Table 7.17. The following indices (CFI= 0.980, IFI= 0.980, TLI= 0.967, RMSEA= 0.086 and SRMR = 0.0321) indicate the model fit is acceptable. All coefficients of SRW were larger than 0.7, proving strong loadings. The results showed that the AVE value exceeded 0.5, thus confirming convergent validity. Discriminant validity was also supported, as the square root of AVE $\sqrt{AVE} = 0.885$ was greater than the highest correlation (r = 0.801) between decision-maker innovativeness and project champion.

Table 7.17 : CFA Outcomes for Human Constructs

Items	**SRW**	**AVE**	**$\sqrt{\text{AVE}}$**	**Highest Construct Correlation**	**Model Fit**
HF_INN_Q1	0.786	0.784	0.885	0.801	CFI= 0.980 IFI= 0.980 TLI= 0.967 RMSEA= 0.086 SRMR = 0.0321
HF_INN_Q2	0.892				
HF_INN_Q3	0.833				
HF_PC_Q1	0.866				
HF_PC_Q2	0.935				
HF_PC_Q3	0.908				
HF_EC_Q2	0.874				
HF_EC_Q3	0.825				

7.5.5 Reliability and Validity: Adoption Barriers

Two factors were identified within the adoption barriers: lack of technological knowledge (LTK) and regulatory uncertainty (RU). Table 7.18 provides the outcomes of the EFA Pattern Matrix. The KMO value for the two constructs was 0.779, which exceeds the 0.7 threshold and a cumulative variance of 86.398%. All commonalities were above the threshold of 0.4. It was observed that there were no issues with cross-loadings. Therefore, all data were retained for reliability assessment.

Table 7.18 : EFA Pattern Matrix for Adoption Barriers

		Component	
Items	**Communality**	**1**	**2**
BF_LTK_Q1	0.844	0.931	
BF_LTK_Q2	0.858	0.844	
BF_LTK_Q3	0.784	0.896	
BF_RU_Q1	0.909		0.902
BF_RU_Q2	0.925		0.994

Note: KMO=0.779, p<0.01

Rotation converged in 3 iterations.

The internal consistency of the retained data related to the barriers-related construct was assessed using Cronbach's alpha and composite reliability following EFA, as presented in Table 7.19. The results indicate high reliability across all constructs; therefore, all five were retained for CFA.

Table 7.19 : Reliability Test for Adoption Barriers Constructs

Construct	**Items**	**Cronbach's alpha**	**CR**
LTK	3	0.894	0.897
RU	2	0.893	0.910

Table 7.20 shows the CFA results for all the retained constructs. The following indices (CFI= 0.992, IFI= 0.992, TLI= 0.998, RMSEA= 0.024, SRMR = 0.0097) indicate the model fit is acceptable. All coefficients of standardised regression weight (SRW) were larger than 0.7, indicating strong loadings. The results showed that the AVE value exceeded 0.5, thus confirming convergent validity. The results also confirmed discriminant validity by showing that $\sqrt{AVE} = 0.921$ was greater than the highest correlation (r = 0.644).

Table 7.20 : CFA Outcomes for Adoption Barriers Constructs

Items	**SRW**	**AVE**	$\sqrt{\textbf{AVE}}$	**Construct Correlation**	**Model Fit**
BF_LTK_Q1	0.872				CFI= 0.999
BF_LTK_Q2	0.920				IFI= 0.999
BF_LTK_Q3	0.793	0.850	0.921	0.644	TLI= 0.998
BF_RU_Q1	0.980				RMSEA= 0.024
BF_RU_Q2	0.843				SRMR = 0.0097

7.5.6 Collaborative Robot Adoption

Given that the cobot adoption intent dimension consisted of one construct, a reliability assessment was conducted only on this data (Table 7.21). Cronbach's alpha for adoption intent was above 0.7, showing the high internal consistency for this construct. Consequently, this data was retained for the final structural equation modelling (SEM) tests.

Table 7.21 : Reliability Test of the Adoption Intent

Construct	Items	Cronbach's alpha
Collaborative Robots Adoption Intent (AdInt)	4	0.790

7.6 Evaluation of the Structural Model

The final quantitative analysis process included the structural model evaluation in two steps: (1) the multicollinearity test and (2) testing the study hypotheses. The final HCRAM research model consisted of 15 independent factors and one dependent factor, which were tested for causal relationships. The outcomes of the multicollinearity test and the hypothesis tests for each dimension are presented in the following subsections.

7.6.1 Multicollinearity

It refers to the presence of high correlations among independent constructs [146]. In this study, multicollinearity was assessed utilising the tolerance method and variance inflation factor (VIF). As indicated by [148] and [209], the tolerance value should be above or equal to the threshold of 0.1, and the VIF should be below 10. Therefore, as shown in Table 7.22, all 15 independent constructs meet acceptable levels for tolerance ($\geq$ 0.1) and VIF ($<$ 10). Consequently, no multicollinearity issues were observed in the results.

Table 7.22 : Multicollinearity Test of Independent Constructs

	Tolerance	**VIF**
Relative Advantage	0.590	1.694
Compatibility	0.464	2.156
Trialability	0.631	1.585
Observability	0.280	3.570
Complexity	0.294	3.405
Top Management Support	0.403	2.479
Organisational Readiness	0.336	2.980
Workforce Empowerment	0.311	3.217
Government Support	0.609	1.643
Competitive Pressure	0.356	2.807
decision-maker Innovativeness	0.224	4.460
Project Champion	0.320	3.128
Employee Capability	0.468	2.138
Lack of Technological Knowledge	0.233	4.300
Regulatory Uncertainty	0.639	1.565

7.6.2 Hypothesis Testing: Technology Dimension

The technology dimension model demonstrated a highly significant effect ($R^2 = 0.822$, $p < .001$). The analysis found three of the five factors significantly influence adoption intent (see Table 7.23). H1e complexity showed the strongest relationship ($\beta = -0.519$, $p < 0.001$), then H1b compatibility ($\beta = 0.299$, $p < 0.001$) and H1d observability ($\beta = 0.152$, $p = 0.004$). The analysis also indicated that two factors, H1a relative advantage ($\beta = 0.008$, $p = 0.845$) and H1c trialability ($\beta = 0.063$, $p = 0.080$) had no impact on adoption intent. Figure 7.1 shows the structural model for technology factors.

Table 7.23 : Results of the Structural Relationship for Technology Factors

Relationship	**Hypothesis**	**Influence Direction**	**Standardised Regression**	**T statistics**	**p-value**	**Result**
RA → AdInt	H1a	Positive	0.008	0.271	0.845	Not Supported
COM → AdInt	H1b	Positive	0.299	6.556	0.001	Supported
TRI → AdInt	H1c	Positive	0.063	2.122	0.080	Not Supported
OBS → AdInt	H1d	Positive	0.152	6.515	0.004	Supported
CPX → AdInt	H1e	Negative	-0.519	-12.391	0.001	Supported
Note: $R^2 = 0.822$ (82.2%), p <0.001						

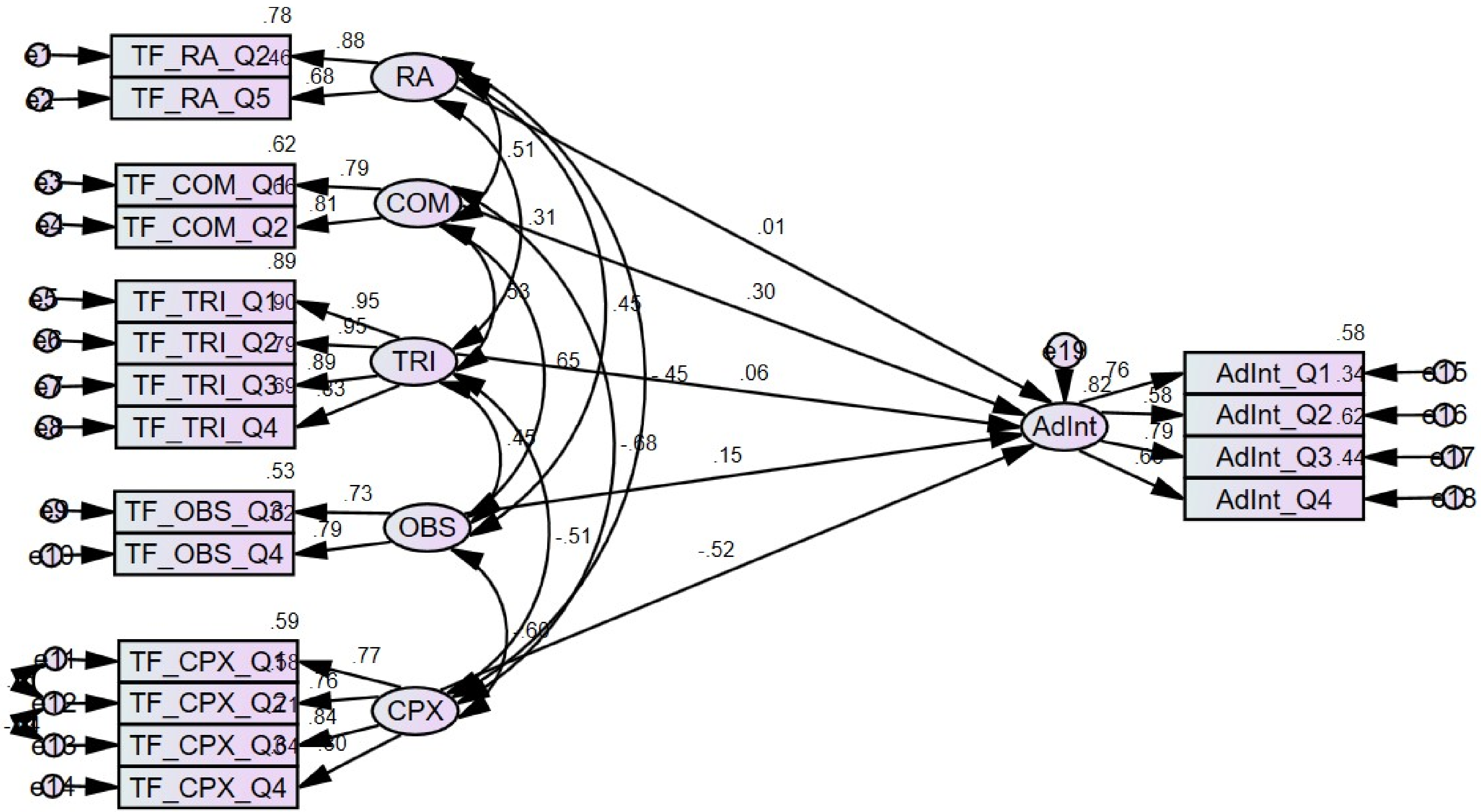


Figure 7.1 : Structural Model for Technology Factors

7.6.3 Hypothesis Testing: Organisational Dimension

The organisational dimension model demonstrated a highly significant effect ($R^2 = 0.833$, $p < .001$). All three factors significantly influenced adoption intent (see Table 7.24). H2c workforce empowerment demonstrated the strongest relationship ($\beta = 0.585$, $p < 0.001$), followed by H2b organisational readiness ($\beta = .283$, $p < .001$) and H2a TMS ($\beta = 0.103$, $p = .038$). Figure 7.2 displays the structural model for organisational factors.

Table 7.24 : Results of the Structural Relationship for Organisational Factors

Relationship	**Hypothesis**	**Influence Direction**	**Standardized Regression**	**T statistics**	**p-value**	**Result**
TMS → AdInt	H2a	Positive	0.103	4.929	0.038	Supported
ORA → AdInt	H2b	Positive	0.283	9.693	0.001	Supported
EMP → AdInt	H2c	Positive	0.585	10.351	0.001	Supported
$R^2 = 0.833$ (83.3%), p <0.001						

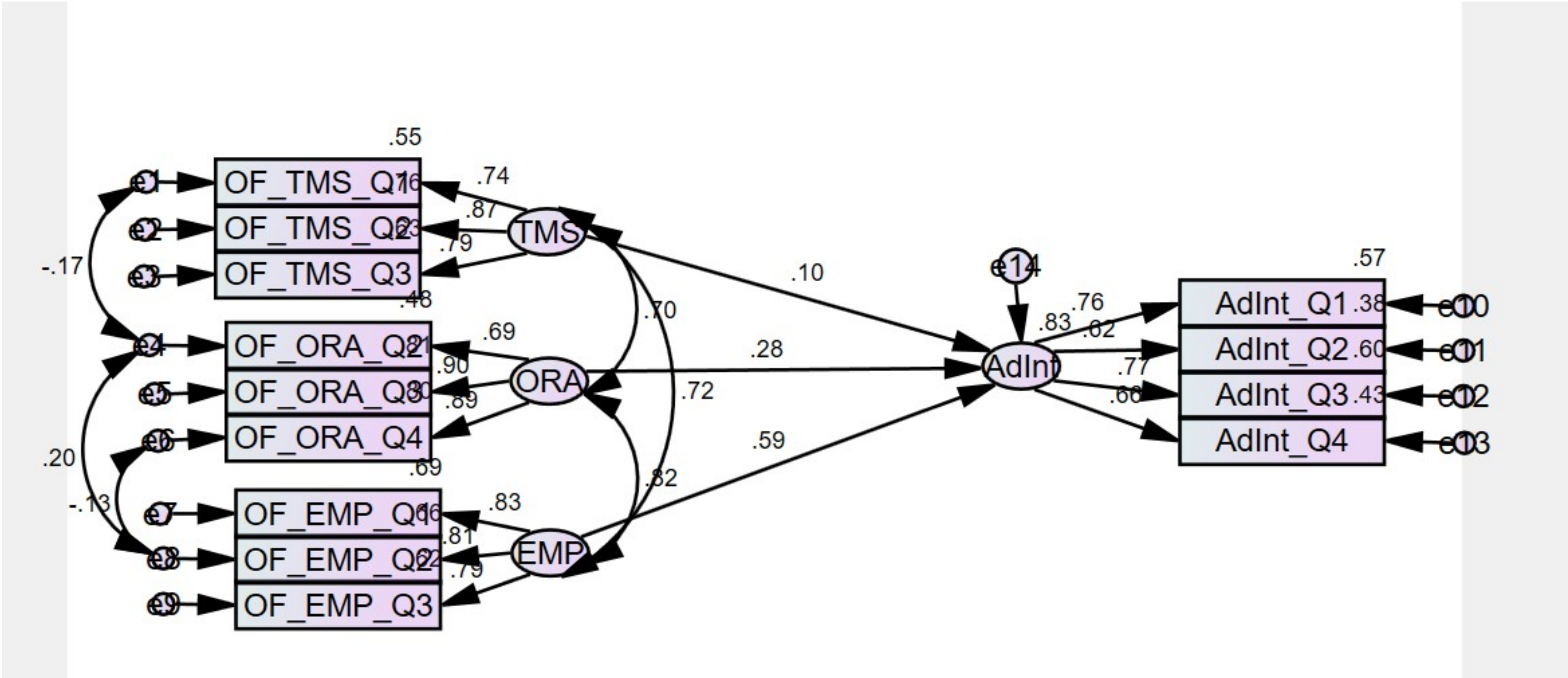


Figure 7.2 : Structural Model for Organisational Factors

7.6.4 Hypothesis Testing: Environmental Dimension

The environmental dimension model demonstrated a highly significant effect ($R^2 = 0.566$, $p < 0.001$). Both factors showed a positive and significant relationship to adoption intent (see Table 7.25). H3a Government support showed the strongest relationship ($\beta = .431$, $p < 0.001$) followed by H3b competitive pressure ($\beta = 0.200$, $p = 0.007$). The structural model for the environmental dimension is illustrated in Figure 7.3

Table 7.25 : Results of the Structural Relationship for Environmental Factors

Relationship	**Hypothesis**	**Influence Direction**	**Standardised Regression**	**T statistics**	**p-value**	**Result**
GS $\rightarrow$ AdInt	H3a	Positive	0.431	10.991	0.001	Supported
CP $\rightarrow$ AdInt	H3b	Positive	0.200	3.328	0.007	Supported
$R^2 = 0.566$ (56.6%), p <0.001						

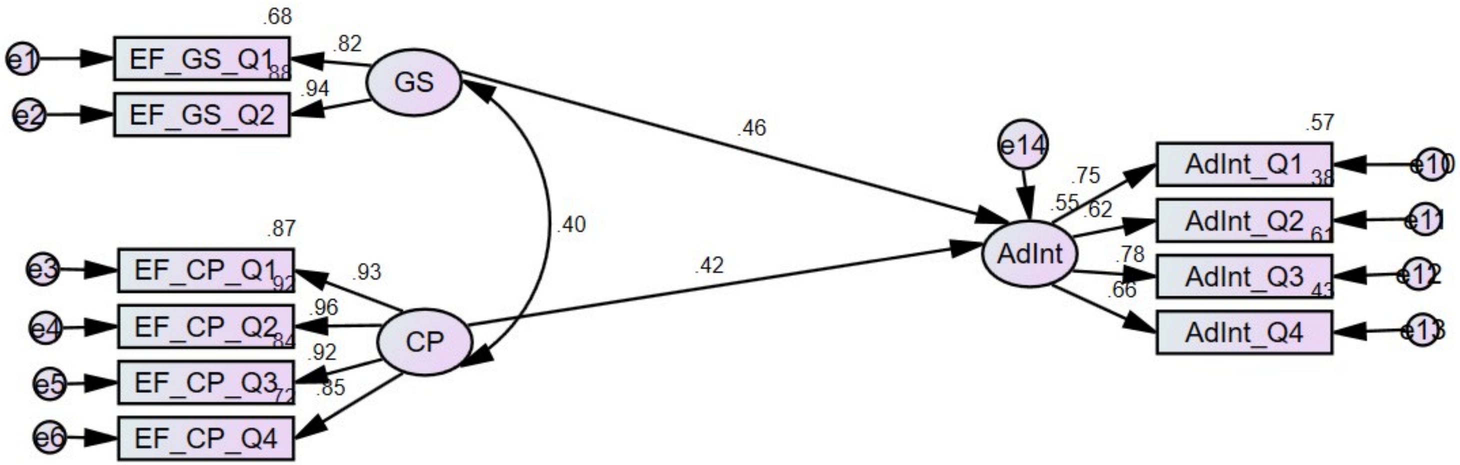


Figure 7.3 : Structural Model for Environmental Factors

7.6.5 Hypothesis Testing: Human Dimension

The human dimension model demonstrated a highly significant effect ($R^2 = 0.95$, $p < 0.001$). The analysis found two of the three factors significantly influence adoption intent (see Table 7.26). H4a decision-maker Innovativeness showed the strongest relationship ($\beta = 0.664$, $p < 0.001$), followed by H4b project champion ($\beta = 0.299$, $p < 0.001$). The analysis also indicated that one factor, H4c employee capability ($\beta = 0.058$, $p = 0.203$) had no impact on adoption intent. Figure 7.4 shows the structural model for the human dimension.

Table 7.26 : Results of the Structural Relationship for Human Factors

Relationship	**Hypothesis**	**Influence Direction**	**Standardised Regression**	**T statistics**	**p-value**	**Result**
INN → AdInt	H4a	Positive	0.664	13.973	0.001	Supported
PC → AdInt	H4b	Positive	0.299	9.810	0.001	Supported
EC → AdInt	H4c	Positive	0.058	3.000	0.203	Not Supported
$R^2 = 0.95$ (95.0%), p <0.001						

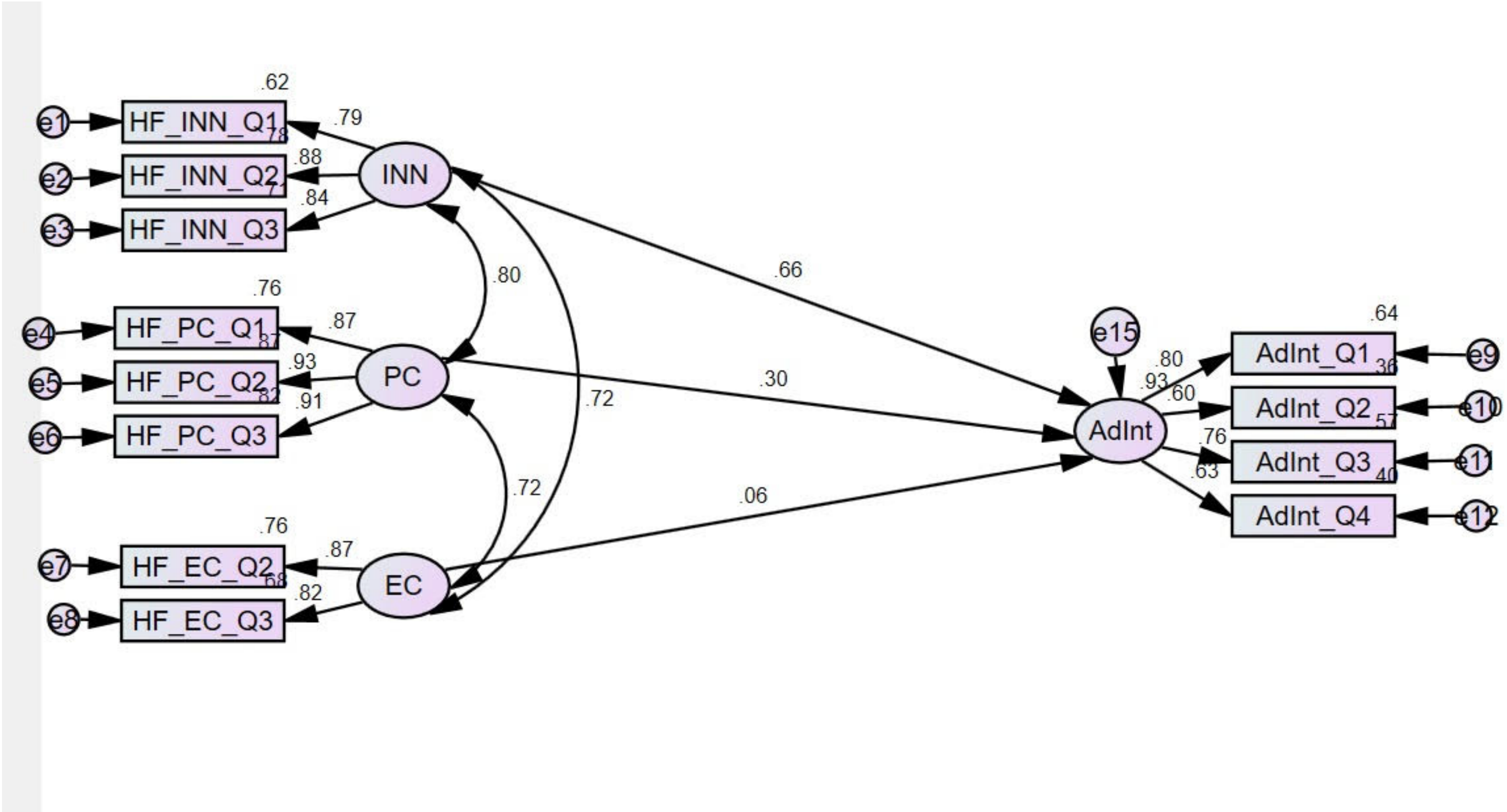


Figure 7.4 : Structural Model for Human Factors

7.6.6 Hypothesis Testing: Adoption Barriers

The Adoption Barriers dimension model demonstrated a highly significant effect ($R^2 = .844$, $p < 0.001$). The analysis found that one of the two factors significantly influences adoption intent (see Table 7.27). As predicted, all hypotheses were negative relationships. H5a Lack of technological knowledge had the strongest relationship ($\beta = -0.907$, $p < 0.001$). However, H5b regulatory uncertainty had no impact on adoption intent ($\beta = -0.018$, $p = 0.641$). Figure 7.5 displays the structural model for the adoption barriers.

Table 7.27 : Results of the Structural Relationship for the Adoption Barriers

Relationship	**Hypothesis**	**Influence Direction**	**Standardised Regression**	**T statistics**	**p-value**	**Result**
LTK → AdInt	H5a	Negative	-0.907	-22.700	0.001	Supported
RU → AdInt	H5b	Negative	-0.018	-3.597	0.641	Not Supported
$R^2 = 844$ (84.4%), p <0.001						

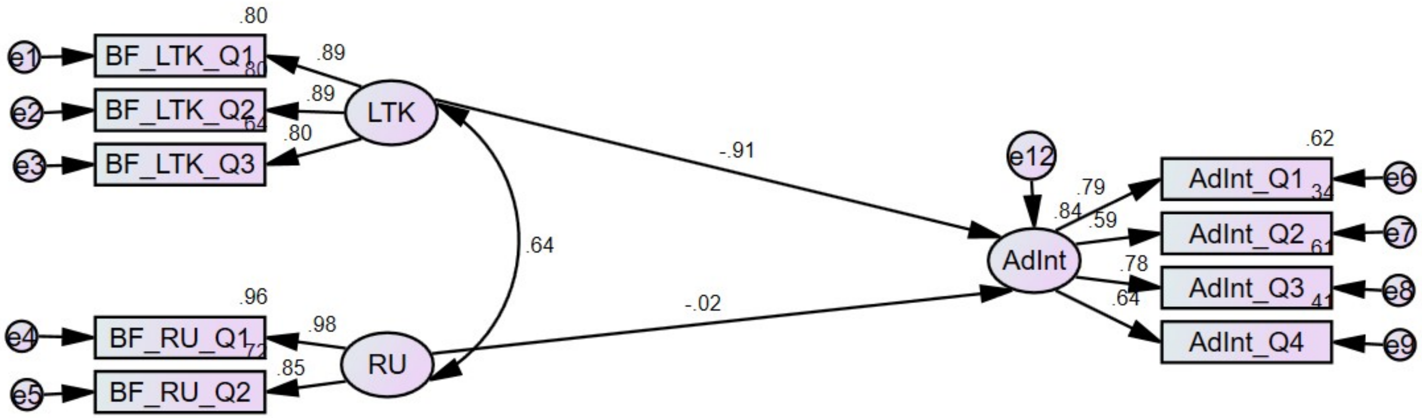


Figure 7.5 : Structural Model for the Adoption Barriers

7.7 Summary

A detailed analysis of the data gathered during the survey is provided in this chapter. The final questionnaire which involves key factors and measurement items, was detailed. This chapter provided descriptive statistics for the sample and performed initial analyses to ensure data quality. All factors demonstrated high reliability and validity. Of the 15 hypotheses, 11 were supported by the SEM results: 3 for the technology dimension (H1b, H1d, H1e), 3 for the organisational dimension (H2a, H2b, H2c), 2 for the environmental dimension (H3a, H3b), 2 for the human dimension (H4a, H4b), one for the Adoption Barriers (H5a). The remaining five hypotheses (H1a, H1c, H4c, H5b) were not supported. Based on the research findings, Chapter 8 presents a detailed discussion.

Chapter 8

Discussion

8.1 Overview

Chapter 8 presents a thorough interpretation of the research's outcomes. To link the thesis aim and objectives, the outcomes of the quantitative and qualitative analyses are combined as follows: first, to explore the key factors and barriers affecting cobot adoption in manufacturing SMEs; second, to develop and refine an HCRAM that supports effective cobot adoption; and third, to evaluate the testing of these factors and the overall dimension for each on cobot adoption. In addressing the outcomes with the primary research question, this thesis revisits the main hypotheses and investigates their evolution throughout the process 8.2. These developments were implemented after the refinement of the proposed HCRAM, as presented and analysed in Chapter 6. An overview of the mixed-method results from Phase 1 and Phase 2 of this thesis is presented in Section 8.3. The outcomes related to the research sub-questions and hypotheses are presented in Sections 8.4 to 8.5. These sections highlight and discuss the key relationships observed.

8.2 Addressing the Study Questions and Objectives

The current work is structured around the following main research question:
How to develop a holistic cobot adoption model for Australian manufacturing SMEs?
The development of HCRAM was informed by the six-step process of the Design Science approach, as outlined by [68].

1. A comprehensive review of existing studies enabled the identification of key knowledge gaps, including the limited presence of an holistic model for cobot adoption precisely tailored for manufacturing SMEs. While some prior studies

have proposed adoption models, they vary significantly in context, methodology, and scope, and often fail to comprehensively address the factors and barriers specific to SMEs. These inconsistencies and limitations highlighted the need for a more focused investigation. Consequently, the key research question was formulated and further divided into sub-questions

2. The study objectives were formulated to facilitate the development of a practical model for cobot adoption in manufacturing SMEs. The resources used to achieve these objectives included existing empirical research on cobot adoption, insight from management and technical experts, and a questionnaire designed to validate these factors within the proposed model.

3. The development of the model followed a multi-stage process. First, the theoretical works on cobot adoption and the broader manufacturing context were reviewed to adopt a relevant theoretical grounding and to determine the key dimensions and barriers, namely technological, organisational, and environmental. Second, the organisational-level technology adoption theories (TOE-DOI) were merged to present a holistic understanding of adoption. Third, a review of empirical works was undertaken to determine the particular detriments within each dimension that significantly affect cobot adoption.

4. The proposal was presented to decision-makers, comprising management and technical experts, for assessment and analysis. During the interviews, the decision-makers identified the most promising applications of the proposed model in manufacturing SMEs. Based on their feedback, the model was revised by merging further factors and deleting those considered less relevant to the SME manufacturing context.

5. Following the refinement of the HCRAM model based on expert feedback, it was examined and validated through a questionnaire conducted with a large sample of manufacturing SME experts, encompassing both management and technical specialists. The model's effectiveness in studying cobot adoption in manufacturing SMEs was confirmed following the evaluation stage.

6. The findings, following the model's refinements and evaluation, are presented and discussed in this thesis. Further dissemination of the results is planned through a series of publications. This process has already commenced with the submission of two qualitative works on the model to an academic conference.

Regarding the evolution of the research sub-questions and objectives, as outlined in Chapter 3, the adoption of cobots in manufacturing SMEs remains limited [23],[54] and not yet mature. However, the scope of the research must be extended and explore empirical works on technology adoption in the manufacturing filed, incorporating factors from the DOI [3] and TOE [4] theories within the manufacturing context. This approach yielded meaningful insights, particularly regarding adoption factors, and facilitated relevant comparisons.

The study acknowledged the varied applications of cobots and the HCRAM was revised based on input from top and mid-level management, as well as technology experts from manufacturing SMEs. Based on the analysis, five dimensions comprising a total of 15 factors were retained due to their relevance. To the author's knowledge, this is the initial model designed to examine and interpret cobot adoption in Australian manufacturing SMEs. The research hypotheses and questions are as follows:

RQ1: What technological factors influence Australian manufacturing SMEs' intention to adopt cobots?

H1a: Relative advantage has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H1b: Compatibility has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H1c: Trialability has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H1d: Observability has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H1e: Complexity has a negative influence on the adoption of cobot technology in Australian manufacturing SMEs.

RQ2: What organisational factors influence Australian manufacturing SMEs' intention to adopt cobots?

H2a: Top management support has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H2b: Organisational readiness has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H2c: Workforce empowerment has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

RQ3: What external factors influence Australian manufacturing SMEs' intention to adopt cobots?

H3a: Government support has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H3b: Competitive pressure has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

RQ4: What human factors influence Australian manufacturing SMEs' intention to adopt cobots?

H4a: The innovativeness of the decision-maker has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H4b: The project champion has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

H4c: Employee capability has a positive influence on the adoption of cobot technology in Australian manufacturing SMEs.

RQ5:What are the barriers that Australian manufacturing SMEs face in adopting cobots?

H5a: A lack of knowledge related to cobot technology negatively affects its adoption in manufacturing SMEs.

H5b: Regulatory uncertainty about cobot technology negatively affects its adoption in manufacturing SMEs.

8.3 Mixed-Methods Results: Comparison and Integration

The HCRAM, with its strong predictive capability, should yield findings consistent with its predictions when examined through a large-scale survey. One of the primary objectives was to develop a functional model of cobot adoption in manufacturing SMEs. The comparison of the mixed-methods findings for each research question is presented in Tables 8.1 to 8.5.

Table 8.1 : Mixed-Methods Findings Comparison for RQ1

Hypotheses	Interviews	Survey	Findings
Hypothesis 1a	Confirmed	Not Confirmed	-
Hypothesis 1b	Confirmed	Confirmed	Positive
Hypothesis 1c	Confirmed	Not Confirmed	-
Hypothesis 1d	Confirmed	Confirmed	Positive
Hypothesis 1e	Confirmed	Confirmed	Negative

Table 8.2 : Mixed-Methods Findings Comparison for RQ2

Hypotheses	Interviews	Survey	Findings
Hypothesis 2a	Confirmed	Confirmed	Positive
Hypothesis 2b	Confirmed	Confirmed	Positive
Hypothesis 2c	Confirmed	Confirmed	Positive

Table 8.3 : Mixed-Methods Findings Comparison for RQ3

Hypotheses	Interviews	Survey	Findings
Hypothesis 3a	Confirmed	Confirmed	Positive
Hypothesis 3b	Confirmed	Confirmed	Positive

Table 8.4 : Mixed-Methods Findings Comparison for RQ4

Hypotheses	**Interviews**	**Survey**	**Findings**
Hypothesis 4a	Confirmed	Confirmed	Positive
Hypothesis 4b	Confirmed	Confirmed	Positive
Hypothesis 4c	Confirmed	Not Confirmed	-
Prior experience	Relationship deleted	-	-

Table 8.5 : Mixed-Methods Findings Comparison for RQ5

Hypotheses	**Interviews**	**Survey**	**Findings**
Hypothesis 5a	Confirmed	Confirmed	Negative
Hypothesis 5b	Confirmed	Not Confirmed	-
Hypothesis 5c	Relationship deleted	-	-
Hypothesis 5d	Relationship deleted	-	-

8.4 Technological Context

8.4.1 Relative Advantage

Although this factor was suggested to have a strong influence in both the cobot and manufacturing contexts and was highlighted in the interviews, the survey did not confirm its effect on cobot technology adoption. Specifically, the results did not indicate a significant impact of relative advantage: ($\beta = 0.008$, $p = 0.845$). However, this outcome is consistent with the results of one recent work in the cobot context [23] and two others in the manufacturing field. The lack of a significant relationship between relative advantage and cobot use can be attributed to several contextual factors. First, although relative advantage is widely validated as a driver of technology adoption in DOI theory, its influence may be less evident when the technology is still perceived as emerging or unfamiliar. In the case of Australian manufacturing SMEs, decision-makers may lack sufficient awareness or exposure to cobots, limiting their ability to evaluate tangible benefits confidently. Furthermore, with cobot adoption remaining relatively limited in Australia, the absence of widespread practical use cases or demonstrable performance improvements may weaken perceived advantages. Finally, SME-specific characteristics, such as resource constraints and risk concerns, may limit organisational and environmental considerations (e.g., cost, skills, external support) over perceived benefits. Therefore, relative advantage alone appears insufficient to substantially influence cobot adoption among Australian manufacturing SMEs at this stage.

8.4.2 Compatibility

Compatibility was perceived during the interviews as a relevant factor in cobot adoption, and this was confirmed by the survey results. Respondents emphasised the importance of cobot compatibility across multiple levels: alignment with manufacturing goals, organisational vision and culture, and integration with existing technical systems. The survey results showed a significant and positive influence ($\beta = 0.299,\ p = 0.001$). This result confirms that when cobot technologies are perceived to align well with existing workflows and systems, decision-makers are more likely to consider adoption. Alignment with the firm's values further supports this decision-making process. For many SMEs, integrating new technologies must not only be technically feasible but also compatible with operational processes without requiring major restructuring.

The strong positive effect of compatibility suggests that cobot solutions perceived as flexible, user-friendly, and customisable are more likely to be favorably received. Given that SMEs often operate with limited resources and lean structures, high compatibility reduces both the cost and disruption of implementation. This outcome is consistent with recent research in the cobot context by [24] and [54], and in the broader manufacturing context by [58],[59],[92],[94]. However, it contrasts with the findings of [23], who reported no significant effect for this factor. Nevertheless, these results confirm that compatibility with existing technology systems remains a critical consideration for cobot adoption in Australian manufacturing SMEs.

8.4.3 Trialability

Trialability was identified in the interviews as potentially facilitating cobot adoption, with several participants suggesting that piloting new technologies on a small scale could lead to broader implementation. However, the survey results did not support the hypothesised relationship ($\beta = 0.063,\ p = 0.080$). This finding is inconsistent with previous research in the cobot context by [24] and [54], suggesting that trialability does not significantly influence cobot adoption among Australian manufacturing SMEs. The lack of a significant effect for trialability may reflect the specific innovation practices within Australian manufacturing SMEs. According to several interviewees, their organisations frequently experiment test new technologies that could enhance operational performance, suggesting that trialing is already an embedded practice rather than a distinctive factor influencing adoption decisions. Furthermore, some respondents indicated that adoption decisions are typically preceded by thorough evaluation processes, meaning that formal trial periods may not always be necessary when strategic interest in the technology is strong. In such cases, the ability to trial becomes less critical to the adoption decision. This context may help explain the findings for cobot adoption in Australian manufacturing SMEs.

8.4.4 Observability

The interviews revealed mixed views on the role of observability in cobot adoption. While some participants considered it an important factor, others saw little relevance, making it difficult to predict its overall influence based on qualitative data alone. However, the survey analysis provided clearer evidence: observability had a statistically significant and positive effect on cobot adoption ($\beta = 0.152,\ p = 0.004$). This finding demonstrates that when cobots are more visible in successful implementations, SME decision-makers are more likely to adopt them. This outcome is consistent with previous research by [24] and [54], which found that the visibility of successful implementation processes enhances innovation adoption. For SMEs with limited internal R&D capabilities, observing tangible outcomes from other firms reduces uncertainty and builds trust in the technology. Therefore, increasing the visibility of successful cobot deployments through case studies, demonstrations, and industry networks could serve as a key policy and industry driver for broader adoption in Australian manufacturing SMEs.

8.4.5 Complexity

Although complexity was identified as a barrier by only five interview participants, their concerns were consistently focused on technical challenges (e.g., programming, system integration) and organisational demands (e.g., training requirements, implementation costs). Despite the limited qualitative emphasis, the survey results revealed that complexity was the strongest negative predictor of cobot adoption ($\beta = -0.519,\ p = 0.001$). This finding aligns with previous research in the cobot context [54] and broader manufacturing studies [59],[104],[105]. The strong negative effect indicates that perceived complexity, whether technical (e.g., programming, integration with legacy systems, safety concerns) or organisational (e.g., workforce training, change management), significantly inhibits adoption among SMEs. Although cobots are generally considered less complex than traditional industrial robots, they still present substantial barriers for resource-constrained SMEs facing long learning curves and potential operational disruptions. This finding suggests that reducing perceived complexity through simplified integration processes, tailored training programs, and effective change management support may be critical for promoting cobot adoption in Australian manufacturing SMEs.

8.5 Organisational Context

8.5.1 Top Management Support

Top management support has been empirically confirmed as a key factor in the adoption of innovation across general manufacturing technologies [59],[91],[92],[97], and specifically in the context of cobots [23],[36],[54]. The survey findings emphasised the relevance of top management support in managing the risks associated with implementing emerging technologies and ensuring successful adoption. However, this was not fully confirmed, as the observed effect was weaker compared with other organisational factors ($\beta = 0.103,\ p = 0.038$). Nevertheless, this result remains plausible in the context of cobot adoption within Australian manufacturing SMEs. The qualitative results revealed that support from top management was described by participants as "crucial" and "imperative". Furthermore, it was identified as the essential factor within the organisational dimension influencing cobot adoption in Australian manufacturing SMEs.

8.5.2 Organisational Readiness

Regarding the qualitative results, the outcomes are consistent with previous studies in the cobot context, which define readiness as the extent to which funding, resources, and technologies are available. In SMEs, readiness challenges are often more pronounced due to limited human resources and fewer innovation teams. Hence, even firms with managerial interest may delay or avoid adoption if readiness gaps are perceived as too wide to bridge.

The survey results also confirmed this factor ($\beta = 0.283,\ p = 0.001$). These findings are consistent with prior works on manufacturing technologies (e.g., [59],[97]) and with recent studies specifically focused on cobots (e.g., [24],[54]).

8.5.3 Workforce Empowerment

In this study, workforce empowerment is considered a distinct factor influencing the cobot adoption process. In the qualitative interviews, participants recognised workforce empowerment as a strong influential factor. Several interviewees observed that when employees are engaged, confident, and given a degree of autonomy in decision-making, they are more likely to support technological change, particularly at this time when it is human-centric. Empowered teams were often described as early adopters of cobot technologies, helping to promote their use across the organisation.

Among all organisational factors in the survey results, workforce empowerment exhibited the strongest effect on cobot adoption intent ($\beta = 0.585,\ p = 0.001$). This shows the important role employees play in influencing technology adoption within SMEs. This link appears to be relatively unique to cobot adoption in manufacturing SMEs, although one study in large-scale manufacturing [20] identified this factor as one of the most enabling for cobot adoption. In other contexts, such as Industry 4.0, this factor has been identified as one of the most important, and its importance has been confirmed [177, 210].

8.6 Environmental Context

8.6.1 Government Support

The qualitative analysis revealed differing views on the importance of government support, based on interview insights. Some participants asserted that the government should primarily focus on supporting development and research programs aimed at motivating manufacturing SMEs to adopt emerging technologies and remain competitive globally. Others argued that government support had only a moderately important influence on adoption, noting that manufacturing SMEs often rely primarily on their internal resources. A few participants clearly believed that government support had minimal impact on cobot adoption. These mixed views are consistent with findings in one study on cobot adoption (e.g. [54]). Furthermore, it was identified as an important factor by [24]. However, the survey results show that government support had a significant positive effect on the intention to adopt cobots in Australian manufacturing SMEs ($\beta = 0.431,\ p = 0.001$). This presents a novel contribution by empirically validating that, within the Australian context, supportive government action is not only desirable but also important for facilitating cobot adoption among SMEs.Similarly, in the broader manufacturing context, the outcomes found by [92] and [91] show that this factor had a significant effect, which is consistent with the present study's findings.

8.6.2 Competitive Pressure

In this study, the qualitative results revealed mixed opinions. Supporters of this factor, consistent with theoretical expectations, referred to the competitiveness that cobots may offer, whereas opponents argued that technology adoption in manufacturing SMEs follows internally planned technology strategies. One study in the cobot context found this pressure had no effect [22]. However, the survey results indicated that this factor is a significant driver of cobot adoption ($\beta = 0.200,\ p = 0.001$). Similarly, one study in the cobot context [24] identified it as one of the most important factors for adoption, and other works in the manufacturing context have confirmed this [59],[91],[92],[97],[105] This suggests that, although Australian SMEs may experience competitive pressure, they may not have the necessary resources or capabilities to respond effectively without external support.

8.7 Human Context

8.7.1 Innovativeness

The outcomes from both the quantitative and qualitative analyses ($\beta = 0.664$, $p = 0.001$) were consistent with these assertions. Interview participants recognised the strong influence of cobots' potential to facilitate successful adoption. This finding aligns with recent quantitative research on cobot adoption (e.g., [36]). Additionally, the study findings are consistent with earlier work by [106] and [107], who identified similar dynamics influencing technology adoption within organisational settings.

8.7.2 Project Champion

Within the human dimension of technology adoption, the existence of a project champion emerges as a context-specific role. The project champion is an individual who acts as an internal advocate, driving the initiative forward by securing support, overcoming resistance, and aligning organisational efforts [168].
The findings supported earlier assertions reflected in both quantitative and qualitative results. Most interviewees confirmed the strong influence of having a project champion, emphasising the individual's key role in actively promoting the adoption process. The survey results further supported the association between project champion and the intention to adopt cobots in Australian manufacturing SMEs ($\beta = 0.299$, $p = 0.001$). This finding aligns with the qualitative results and is consistent with previous research [20],[24].

8.7.3 Employee Capabilities

The qualitative interviews revealed that employee capability emerged as one of the key human strengths driving cobot adoption, as noted by seven interviewees.

They acknowledged the importance of investing in employees, developing their capabilities for the long term, and evaluating the current ones through new programs and initiatives.
Some studies in other technological contexts, such as mobile marketing and digitalisation adoption, identified this factor as an important influence on adoption decisions (e.g., [211],[212]. Nevertheless, the survey analysis revealed no significant relationship between employee capability and adoption intention ($\beta = 0.058$ $p = 0.203$) in Australian manufacturing SMEs. This may suggest that while capability is a concern, it is not currently a critical factor in adoption decisions in Australian manufacturing SMEs. One possible reason is that many SMEs intend to build their skills only after deciding to adopt cobots, often depending on outside suppliers or government training programs. Another explanation could be that most respondents rated their capabilities as similarly low, which reduces their usefulness in explaining differences.

8.8 Adoption Barriers

8.8.1 Lack of Technological Knowledge

In this study, the interview analysis revealed that participants were primarily referring to a lack of knowledge about the technology itself, including how cobots work, how they can be integrated, and the skills required for effective use. Most participants (9 out of 10) identified this as a serious issue in manufacturing SMEs. Consequently, the barrier was renamed *'lack of technological knowledge'* to better reflect its intended meaning. The survey data analysis showed a strongly negative path coefficient ($\beta = -0.907$, $p = 0.001$), indicating that when decision-makers perceive their organisations as lacking the necessary technical knowledge or digital maturity, the likelihood of adopting cobots significantly decreases. This finding aligns with the cobot contex, as highlighted in previous studies [15],[25],[26],[46] which emphasise that limited technological knowledge is a major barrier to adoption.

8.8.2 Regulatory Uncertainty

Uncertainty regarding regulation emerged as another distinctive barrier to cobot adoption in Australian manufacturing SMEs. The interview findings indicated that this lack of clarity was perceived as an obstacle to adoption. This suggests that, even when the technology is accessible, unclear regulatory frameworks can delay decision making. Clearer guidance from regulatory bodies and industry organision may alleviate uncertainty and encourage more confident implementation of cobots in the Australian manufacturing SME sector. However, this factor had no effect in the quantitative phase ($\beta = -0.018$ $p = 0.641$). These findings suggest that, although unclear regulations around cobot deployment are perceived as a challenge, they may not currently be a key factor influencing adoption intent. At this stage, decision-makers are more likely to focus on internal readiness, such as workforce empowerment, or on external enablers, such as government support and technological knowledge, rather than on regulatory frameworks. Regulatory uncertainty may become more relevant during later phases of adoption, particularly during integration or scaling. This outcome is consistent with one work on blockchain adoption (e.g.,[183]).

8.9 Summary

Chapter 8 presents a critical discussion of the study's findings to existing literature on cobot adoption and within the broader context of manufacturing. Of the fifteen hypothesised relationships, eleven were confirmed by the study's findings, indicating that the HCRAM has explanatory capability. In several confirmed respects, the hypotheses were consistent with the literature on cobot adoption and the broader manufacturing context. The unsupported hypotheses may be attributable to the specific study context. Furthermore, three relationships, empowerment, employee capability, and regulatory uncertainty, warrant further investigation in future research. Chapter 9 concludes the thesis and outlines the key implications of this work.

Chapter 9

Conclusion and Future Work

9.1 Overview

Chapter 9 presents the conclusion of this thesis and outlines directions for future research. Section 9.2 summarises the problems addressed in this study, while the research contributions are discussed in Section 9.3. The limitations of the study and directions for future research are presented in Section 9.4.

9.2 Problems Addressed in This Thesis

This study aims to address key gaps identified in Chapter 2 concerning cobots adoption in manufacturing SMEs, as outlined below.

- Existing studies on cobot adoption primarily focus on large manufacturing firms and, in some instances, do not specify firm size. This highlights a gap in the literature regarding the unique adoption factors, challenges, and decision-making processes relevant to the SME context.

- While prior research has identified several factors influencing cobot adoption, the current literature provides only a limited understanding of their combined effects. In particular, there is a lack of comprehensive frameworks that integrate both enabling factors and barriers within a single holistic model, especially in the context of manufacturing SMEs.

- Although only two studies have proposed theoretical frameworks for cobot adoption in manufacturing SMEs, these models show limitations in effectively integrating human factors and barriers with technological, organisational, and external dimensions to provide a comprehensive understanding of the adoption process.

- Of the 14 empirical works on cobot adoption in manufacturing SMEs identified in the systematic literature review, only two employed qualitative approaches and two adopted quantitative designs. These studies also exhibit limitations, including small sample sizes and a predominant focus on managerial perspectives, with limited input from technology experts despite their important role in adoption decisions.

- Finally, there is no existing research that specifically investigates cobot adoption in Oceania, particularly within Australian manufacturing SMEs. Given Australia's distinctive industrial structure, high labour costs, and persistent skill shortages, exploring this context warrants focused investigation. As global interest in cobots continues to grow, especially in countries such as Germany, France, and Portugal, this study provides an initial roadmap for decision-makers in the Australian manufacturing sector.

9.3 Implications and Contributions

Building on the gaps identified in this thesis, the implications and contributions are outlined below.

9.3.1 Practical Implications

- This study provides initial insights into cobot adoption within Australian manufacturing SMEs. While growing interest in cobot technology reflects its potential benefits, it is also accompanied by uncertainty regarding practical applications in SME contexts. A comprehensive understanding of cobot adoption is therefore essential for manufacturing decision-makers seeking to pursue adoption in a strategic and informed manner. The adoption framework developed and tested in this research offers a valuable starting point to support such decision-making.

- This research introduces the first empirically tested, practice-oriented model of cobot adoption in Australian manufacturing SMEs, termed the Holistic Collaborative Robot Adoption Model (HCRAM). To the author's knowledge, this study represents the first effort to examine the integrated effects of human, organisational, technological, environmental, and barrier-related factors on cobot adoption within this context. The model can serve as a practical guide for manufacturing SMEs and potentially the broader manufacturing sector in determining how and when to undertake cobot adoption.

- The proposed HCRAM systematically organises the key factors influencing adoption in Australian manufacturing SMEs into distinct dimensions. This structure enables decision-makers to assess the influence of each dimension and associated variables, both prior to adoption decisions and throughout the implementation process.

- Failure to achieve statistical significance for certain factors does not necessarily imply an absence of influence. Some factors may still affect cobot adoption; however, their role may be less evident during the early stages of the adoption process.

- Although HCRAM was originally developed in the context of cobot applications in assembly processes, the the framework can be adapted to assess both internal and external effects on cobot adoption. This flexibility allows decision-makers to identify and prioritise critical factors, thereby supporting more targeted and effective adoption strategies.

9.3.2 Theoretical Implications

- The outcomes of this research confirm the applicability of the Science Design approach for modelling cobot adoption within Australian manufacturing SMEs.

- The results validate the DOI-TOE framework as a viable tool for investigating cobot adoption in Australian manufacturing SMEs, with the majority of hypotheses aligning with established findings. This supports the theoretical applicability of TOE and DOI when extended to a novel context, namely Australian manufacturing SMEs.

- The study further confirmed the adaptability of the DOI-TOE framework by extending it to incorporate contextual features. This extension demonstrates the framework's flexibility and contributed to its theoretical refinement by highlighting the importance of factors that have previously been overlooked in adoption studies.
- By validating an instrument to investigate cobot adoption, the research contributes methodological tools capable of capturing both combined and dimension-specific effects in Australian manufacturing SMEs.

9.4 Limitations and Future work

As with any empirical investigation, this study has several limitations that should be considered when interpreting its findings.

- The study is limited to the Australian context.
- It focuses exclusively on manufacturing SMEs.
- As cobot adoption in Australian manufacturing SMEs remains at an early stage, some participants may not have had comprehensive knowledge of the technology, which could have affected the accuracy of their responses.
- The research adopts a cross-sectional design, which limits the ability to capture changes in adoption behaviour over time.

For future research, this study several areas that need further investigation.

- Future studies could expand adoption models by placing greater emphasis on human (individual) factors. Variables such as trust in technology, perceived job security, and skill adaptability require further investigation.
- Contrary to expectations, relative advantage did not demonstrate a significant positive effect on cobot adoption. This suggests that in the early stages of diffusion, decision-makers may prioritise perceived benefits over other attributes, a pattern that warrants further empirical investigation.

- Future research could benefit from developing and testing alternative conceptual models informed by the perspectives of technology experts and industry practitioners. Expert-driven frameworks may help refine factor specifications, improve model accuracy, and enhance the applicability of adoption models across different organisational contexts.
- Applying longitudinal research designs would allow future studies to capture changes in adoption behaviour over time and provide deeper insights into the dynamics of cobot adoption.

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Appendices

Appendix A: Phase 1 (Qualitative Research): Interview Questions

UNIVERSITY OF TECHNOLOGY SYDNEY

Interview Questions

Firstly, thank you for your participation, which is most appreciated. I am Mashael Haddas, a PhD candidate at the University of Technology Sydney (UTS). I am conducting a research study for my PhD thesis under the supervision of Professor Farookh Khadeer Hussain. The main purpose of my research study is to develop and improve a comprehensive collaborative robots (cobots) adoption framework that Australian manufacturing small and medium-sized enterprises (SMEs) could use. So, today's interview aims to explore your knowledge and perceptions of collaborative robot adoption in manufacturing SMEs. The interview will take about 45 min to 1 hour.

The interview will be recorded and subsequently de-identified via the creation of an interview transcript. You have an opportunity to review the transcript to ensure the accuracy of the data and redact any information you do not wish to be included in the research. All this information will be treated confidentially, and only the researchers involved in this project will have access to the information. Your information will only be used for the purpose of this research project, and it will only be disclosed with your permission, except if required by law. The supervisor and I will analyse and discuss the results for academic purposes. In any subsequent publications, information will be provided in such a way that you cannot be identified.

Do you agree with this?

Do you have any questions before we begin?

Interview Questions

Do you agree with this?

Do you have any questions before we begin?

Part1:Personal Information:

- Your organisation size.
- What is your position?
- How long have you been in your job?
- What type of factory do you work in?

Part 2: Questions related to Collaborative robots in Australian manufacturing SMEs:

1. To what extent do you think collaborative robots are currently being developed and used in Australian manufacturing SMEs? Why do you think this?

2. Name what you think are the most promising collaborative robot applications for Australian manufacturing SMEs. Why this/these particular application/s?

3. What technological factors are, in your opinion, most important in adopting collaborative robots, and why? Examples: relative advantage, compatibility, observability, complexity, etc.

4. What organisational factors are, in your opinion, most important in adopting collaborative robots, and why? Examples: top management support, organisational readiness, etc.

5. What context (environmental) factors are, in your opinion, most important in adopting collaborative robots, and why? Examples: government support, competitive pressure, etc.

6. What human factors are, in your opinion, most important in adopting collaborative robots, and why? Examples: a presence of a champion (project champion), prior experience, decision-maker innovativeness, etc.

7. In your opinion, what are the significant difficulties/barriers that impact the adoption and use of collaborative robots in your organisation? Examples: safety issues, lack of knowledge, fear of job loss, etc.

8. Do you have anything to add?

Appendix B: Phase 1 (Qualitative Research): Information Sheet and Consent Form for Participants

Participant Information Sheet and Consent Form For Interviews

[ETH22-7564]

Dear participant,

My name is Mashael Ali Haddas and I am a Ph.D. candidate at the University of Technology Sydney (UTS). My supervisor is Prof. Farookh Hussain.

The main purpose of my research study is to develop and improve a comprehensive collaborative robots (cobots) adoption framework that Australian manufacturing small and medium-sized enterprises (SMEs) could use. The outcomes of this research will have both theoretical and practical implications in the field of manufacturing SMEs. This study will also benefit manufacturing SMEs, as they will better understand the potential challenges to collaborative adoption in Australian manufacturing SMEs.

You have been invited to participate in this study due to your knowledge and experience.

- The activity will take place online (UTS Zoom online).
- You will participate in a 45-minute to one-hour semi-structured interview that will be audio-recorded and transcribed to ensure the validity of the analysis. The advantage of audio recording the interview is that it allows the researcher to make general notes while the participant speaks. Therefore, the researcher is able to focus on the interview rather than writing down the details of every answer. However, some of the participants may prefer that their interview is not recorded, in which case, the researcher will write down each answer. The participant will have the opportunity to review the transcript of their interview.

Your participation in this research involves little risk or no risk.

Participation in this study is voluntary. It is up to you to decide whether to participate or not.

If you decide not to participate or to withdraw from the study, it will not affect your relationship with the researchers or the University of Technology Sydney.

If you wish to withdraw from the study once it has started, you can do so at any time without having to give a reason by contacting Mashael Haddas [Mashael.Haddas@student.uts.edu.au] or Prof. Farookh Hussain[Farookh.Hussain@uts.edu.au]. If you withdraw from the study, there will be no penalty, and all information that you have provided will remain confidential and be stored in line with UTS regulations. Personal details will not be stored.

By signing the consent form, you consent to your information being collected for the research project. This information will be treated confidentially and will be stored in line with UTS regulations.

It is anticipated that the results of this research project will be published and/or presented in various forums. In any publication and/or presentation, information will be provided in such a way that you cannot be identified.

Following relevant Australian and/or NSW privacy laws, you have the right to request access to information about you which has been collected and stored by the research team. You also have the right to request that any information with which you disagree be corrected. Please inform either Mashael Haddas or Prof.Farookh if you would like to access your information.

The results of this research may be shared through open-access (public) scientific databases, including Internet databases. This will enable other researchers to use the data to investigate other important research questions. Results shared this way will always be de-identified by removingall personal information (e.g. name, address, date of birth, etc.).

If you have any queries or concerns about the research, please feel free to contact me at Mashael.Haddas@student.uts.edu.au , +6146[redacted]], or my supervisor Prof. Farookh Hussain on Farookh.Hussain@uts.edu.au, +6140[redacted]
You will be given a copy of this form to keep.

NOTE:

This study has been approved in line with the University of Technology Sydney Human Research Ethics Committee [UTS HREC] guidelines. If you have any concerns or complaints about any aspect of the conduct of this research that you wish to raise independently of the research team, please contact the Ethics Secretariat on ph. +61 2 9514 2478 or email [Research.Ethics@uts.edu.au] and quote the Ethics Approval number **ETH22-7564**. Any matter raised will be investigated confidentially, and you will be informed of the outcome.

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CONSENT FORM

I______________________[participant's name] agree to participate in the research project being conducted by [Mashael Haddas [Mashael.Haddas@student.uts.edu.au] Phone: +6146[redacted]; and Prof. Farookh Hussain [Farookh.Hussain@uts.edu.au] Phone +6140[redacted].

I have read the Participant Information Sheet. I understand the purposes, procedures and risks of the research as described in the Participant Information Sheet.

I have had an opportunity to ask questions, and I am satisfied with the answers I have received.

I freely agree to participate in this research project as described and understand that I am free to withdraw at any time without affecting my relationship with the researchers or the University of Technology Sydney.

I understand that I will be given a signed copy of this document to keep.

I am aware that I can contact Mashael Haddas and Prof. Farookh Hussain if I have any concerns about the research.

______________________________________ ____/____/

Name and Signature [participant] Date

Mashael Haddas / /

Name and Signature [researcher or delegate] Date

Appendix C: Phase 2 (Quantitative Research): Information Sheet and Consent Form for Participants

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

Information Sheet and Consent Form For Questionnaire

[ETH24-9468] - Collaborative Robot Technology Adoption in Australian Manufacturing SMEs

WHO IS CONDUCTING THIS RESEARCH?

My name is Mashael Ali Haddas, and I am a Ph.D. candidate at UTS. My supervisor is Prof. Farookh Hussain (Farookh.Hussain@uts.edu.au)

WHAT IS THE RESEARCH ABOUT?

The purpose of this research/online survey is to identify the factors that influence the adoption of collaborative robots (cobots) technology in Australian manufacturing small and medium-sized enterprises (SMEs). The outcomes of this research will have both theoretical and practical implications in the field of manufacturing SMEs. This development could help improve decision-making by senior management in the Australian manufacturing industry.

You have been invited to participate due to your knowledge and expertise in this area.

Before you decide to participate in this research study, we need to ensure that it is ok for you to take part:

- You are employed at a small or medium-sized manufacturing company.

- You hold a decision-making role within your company, whether in a top management position, a middle management position, or as a technical specialist.

WHAT DOES MY PARTICIPATION INVOLVE?

Participation in this study is voluntary. It is completely up to you whether or not you decide to take part.

If you decide to participate, I invite you to continue answering the survey questions. The survey should take about 15 minutes of your time.

You can change your mind anytime and stop completing the survey/s without consequences.

ARE THERE ANY RISKS/INCONVENIENCE?

We don't expect this questionnaire to cause any harm or discomfort. However, if you experience discomfort or distress answering the questions, please contact me (au) +6146[redacted] or via email Mashael.Haddas@student.uts.edu.au. My supervisor is Prof. Farookh Hussain, Farookh.Hussain@uts.edu.a

WHAT WILL HAPPEN TO INFORMATION ABOUT ME?

Your responses will be kept entirely confidential and will only be used for academic purposes. Submission of the online questionnaire/s is an indication of your consent.

The process of data collection will take place in a highly confidential manner and the participants' identities will be kept anonymous. The data will only be utilized for the purpose of this research.

All collected data will be securely stored on Quartilcs with access restricted to the research team.

In accordance with relevant Australian and/or NSW Privacy laws, you have the right to request access to the information about you that is collected and stored by the research team. You also have the right to request that any information with which you disagree be corrected. Please inform the research team member named at the end of this document if you would like to access your information. This will only be possible if you provide personal information which may individually identify you, or be reasonably identifiable (e.g. if any open-text responses contextually identify or re-identify you).

It is anticipated that the results of this research project will be published and/or presented in a variety of forums. The results of this research may also be shared through open-access (public) scientific databases, including internet databases. This will enable other researchers to use the data to investigate other important research questions. Results shared in this way will always be de-identified by removing all personal information (e.g. your name, address, date of birth, etc.) and/or any contextual information that could identify you.

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

WHAT IF I HAVE ANY QUERIES OR CONCERNS?

If you have any queries or concerns about the research that you think my supervisor or I can help you with, please feel free to contact me (au) +6146[redacted] or via email Mashael.Haddas@student.uts.edu.au My supervisor is Prof. Farookh Hussain, Farookh.Hussain@uts.edu.a.

If you would like to talk to someone who is not connected with the research, or if you have any concerns or complaints about any aspect of the conduct of this research that you wish to raise independently of the research team, please contact the Ethics Secretariat on 02 9514 2478 email or Research.ethics@uts.edu.au and quote this number ETH24-9468. Any matter raised will be treated confidentially, investigated and you will be informed of the outcome.

Appendix D: Phase 2 (Quantitative Research): Online Questionnaire

A brief explanation of collaborative robots (cobots) technology

A collaborative robot (cobot) is a robotic device that works in a manufacturing environment alongside humans without safety barriers or fences. Collaborative robots are small in size, light in weight, flexible and affordable, which are appropriate for SMEs to produce customized, small batch products and pay attention to the return on investment (ROI). Collaborative robots are used in various potential manufacturing applications, such as machine tending, material handling, packaging and labelling, and small batch production. Today, the most popular application is collaborative robots for assembly processes, as they can perform a wide range of tasks by smoothly switching from one task to another with minimal setup time by adjusting their tooling or programming. For a more detailed explanation, refer to: https://www.youtube.com/watch?v=uqdrlXuIEFM

Please do not hesitate to contact me at Mashael.Haddas@student.uts.edu.au, if you require additional clarification or have questions.

Part 1: About You (Demographic Information and Knowledge of Collaborative Robots)

1. Educational level:
   - o High school
   - o Diploma
   - o Bachelor degree
   - o Postgraduate degree

2. Your job position:
   - o Top Management (e.g., owner, President, CEO, Director, General Manager, etc.)
   - o Middle Management (e.g., Production Manager, Plant Manager, Operations Managers, etc.)
   - o Technology Specialists (e.g., CTO, IT Manager, Automation Engineer, Robotics Engineer, etc.)
   - o Other (please specify):………………..

3. Where is your company located?
   - o Australian Capital Territory
   - o New South Wales
   - o Victoria
   - o QLD
   - o Western Australia
   - o South Australia
   - o Northern Territory
   - o Tasmania

4. How many employees work in your company (approx.)?
   - o 0- 4 employees
   - o 5 -19 employees
   - o 20 -199 employees

5. What is your level of knowledge of collaborative robots?
   - o No knowledge
   - o Some knowledge
   - o Good knowledge

Skip To: End of Block If What is your level of knowledge about collaborative robots? =No knowledge

Part 2: Collaborative Robots Adoption Factors

Technological Factors

1. Please rate the degree to which you agree with each statement (Relative Advantage) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
RA1: Collaborative robot technology will enable assembly processes to be managed effectively.							
RA2: The adoption of collaborative robot technology will enable assembly processes to be completed more quickly.							
RA3: The adoption of collaborative robot technology will increase the productivity of our assembly processes.							
RA4: The adoption of collaborative robot technology will improve the performance of our assembly processes.							
RA5: The adoption of collaborative robot technology will increase the profitability of our assembly processes.							

2. Please rate the degree to which you agree with each statement (Compatibility) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
COM1: Collaborative robot technology will fit the work style of our assembly processes.							
COM2: Collaborative robot technology will be completely compatible with the current assembly processes.							
COM3: Using collaborative robot technology in the assembly processes will be compatible with our company's culture and value system.							
COM4: Using collaborative robot technology in the assembly processes will be compatible with our manufacturing company's existing hardware and software.							

3. Please rate the degree to which you agree with each statement (Trialability) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
TR1: It will be possible to trial collaborative robot technology in the assembly processes at our company.							
TR2: Our company will permit the use of collaborative robot technology for assembly processes on a trial basis to evaluate its performance.							
TR3: Our company would prefer to trial collaborative robot technology for assembly processes before fully							

implementing the technology.							
TR4: A successful trial of collaborative robot technology for assembly line tasks will be a key element in deciding to implement it.							

4. Please rate the degree to which you agree with each statement (Observability) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
OB1: The benefits of collaborative robot technology for assembly processes can be easily observed.							
OB2: We are aware of collaborative robot use for manufacturing assembly processes.							
OB3: It is observed that companies in the same industry are adopting collaborative robot technology.							
OB4: Many of our competitors and business partners in the market have started using collaborative robot technology.							
OB5: Using collaborative robot technology for assembly processes has produced improved results compared to traditional business practices.							

5. Please rate the degree to which you agree with each statement (Complexity) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
CPX1: The skills required to adopt collaborative robot technology for assembly processes could be complicated for our manufacturing company.							
CPX2: The skills required to adopt collaborative robot technology for assembly processes could be complicated for our employees.							
CPX3: Integrating collaborative robot technology into our current work practices will be challenging.							
CPX4: Our company may encounter some difficulties in maintaining the collaborative robot system for assembly processes.							

Organisational Factors

1. Please rate the degree to which you agree with each statement (Top Management Support) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
TMS1: Our top management provides timely and sufficient information about							

implementing new technology in our company.							
TMS2: Our top management provides strong leadership when it comes to technology adoption.							
TMS3: Our top management is willing to take the risks involved in collaborative robot adoption.							
TMS4: Our top management is likely to consider the adoption of collaborative robot technology for assembly processes as strategically important.							
TMS5: Our top management supports the implementation of new technologies for the company.							

2. Please rate the degree to which you agree with each statement (Organisational Readiness) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
OR1: Our company constantly seeks new technologies to meet its needs.							
OR2: Our company has sufficient financial resources to adopt collaborative robot technology for assembly processes.							
OR3: Our company has sufficient technical capacity for							

Environmental Factors

1. Please rate the degree to which you agree with each statement (Government Support) for collaborative robot technology.

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
GS1: There would be financial support from the Australian government to adopt collaborative robot technology.							
GS2: The Australian government encourages companies to propose and apply for collaborative robot projects.							
GS3: The Australian government would provide training in collaborative robot-related skills							
GS4: The Australian government sponsors collaborative robot workshops and conferences.							

2. Please rate the degree to which you agree with each statement (Competitive Pressure) for collaborative robot technology.

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
CP1: Competitors influence a company's decision to adopt collaborative robot technology.							
CP2: Our company will experience competitive pressure to adopt							

collaborative robot technology for assembly processes.							
CP3: Some of our competitors have started to adopt collaborative robot technology.							
CP4: Our company could benefit from collaborative robot technology to maintain a competitive position in the market.							

Thank you for your time,
We have only a few questions remaining!

Human Factors

1. Please rate the degree to which you agree with each statement (Decision-Maker Innovativeness) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
INN1: Our company's decision-makers aim to leverage collaborative robots for assembly processes.							
INN2: Decision makers in our company will be keen to experiment with collaborative robots for assembly processes.							
INN3: Decision makers in our company will be confident in trying out collaborative robots for assembly processes.							

2. Please rate the degree to which you agree with each statement <u>(Project Champion)</u> for collaborative robot technology.

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
PC1: Collaborative robots have strong advocates in our company.							
PC2: There are one or more people in our company who are enthusiastically pushing for collaborative robot technology.							
PC3: There are one or more people in our company who are constantly praising the benefits of collaborative robots for assembly processes..							

3. Please rate the degree to which you agree with each statement <u>(Employee Capability)</u> for collaborative robot technology.

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
EC1: Most employees of our company are aware of the importance of introducing collaborative robots for assembly processes.							
EC2: Most employees of our company are willing to learn to use collaborative robots for assembly processes.							
EC3: Most employees of our company will be							

able to use collaborative robots after training.							

Barrier Factors

1. Please rate the degree to which you agree with each statement (Lack of Technological Knowledge) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
LTK1: Our company has little knowledge about how collaborative robots can be used for assembly processes.							
LTK2: Our company still lacks the technical knowledge and skills required to adopt collaborative robot technology for assembly processes.							
LTK3: The technology decision-makers in our company do not fully understand collaborative robot technology for assembly processes.							

2. Please rate the degree to which you agree with each statement (Regulatory Uncertainty) for collaborative robot technology.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
RU1: Our company is concerned that collaborative robot technology will result							

in compliance deficiencies.							
RU2: Using collaborative robot technology for assembly processes will result in new regulations forcing new compliance considerations.							

<u>Adoption intent factor</u>

1. Please rate the degree to which you agree with each statement <u>(Intent to adopt collaborative robot technology for assembly line tasks).</u>

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
AdInt1: Our company is willing to adopt collaborative robot technology for assembly processes.							
AdInt2: Our company will take steps to adopt collaborative robot technology for assembly processes in the near future.							
AdInt3: Our company is ready to invest resources in adopting collaborative robot technology for assembly processes.							
AdInt14: Overall, our company has a favourable attitude toward adopting and using collaborative robot technology for assembly processes.							

Do you have any comments you would like to add?

Appendix E: Descriptive Statistics

Descriptive Statistics

Item	N Statistic	Mean Statistic	Std. Deviation Statistic	Std. Error
TF_RA_Q1	640	5.67	.772	.0305
TF_RA_Q2	640	5.34	1.053	.0416
TF_RA_Q3	640	5.68	.831	.0328
TF_RA_Q4	640	5.84	.850	.0336
TF_RA_Q5	640	5.15	1.203	.0476
TF_COM_Q1	640	5.13	.970	.0383
TF_COM_Q2	640	4.53	1.130	.0447
TF_COM_Q3	640	5.51	1.172	.0463
TF_COM_Q4	640	4.38	1.192	.0471
TF_TRI_Q1	640	3.79	1.371	.0542
TF_TRI_Q2	640	5.18	1.230	.0486
TF_TRI_Q3	640	5.32	1.170	.0463
TF_TRI_Q4	640	4.10	1.042	.0412
TF_OBS_Q1	640	5.30	1.142	.0451
TF_OBS_Q2	640	5.65	.801	.0317
TF_OBS_Q3	640	5.21	1.137	.0449
TF_OBS_Q4	640	4.48	1.440	.0569
TF_OBS_Q5	640	5.78	1.103	.0436
TF_CPX_Q1	640	4.65	1.271	.0502
TF_CPX_Q2	640	5.67	1.453	.0574
TF_CPX_Q3	640	5.34	1.307	.0517
TF_CPX_Q4	640	4.55	1.422	.0562
OF_TMS_Q1	640	4.97	.932	.0368
OF_TMS_Q2	640	5.31	1.118	.0442
OF_TMS_Q3	640	5.23	1.100	.0435
OF_TMS_Q4	640	4.96	1.011	.0399
OF_TMS_Q5	640	4.91	.973	.0385
OF_ORA_Q1	640	4.52	1.134	.0448
OF_ORA_Q2	640	3.81	1.095	.0433
OF_ORA_Q3	640	5.56	1.136	.0449
OF_ORA_Q4	640	5.80	1.193	.0471

OF_ORA_Q5	640	4.94	1.009	.0399
OF_EMP_Q1	640	5.70	1.143	.0452
OF_EMP_Q2	640	5.20	1.053	.0417
OF_EMP_Q3	640	5.67	1.026	.0405
EF_GS_Q1	640	4.89	1.073	.0424
EF_GS_Q2	640	3.98	1.369	.0542
EF_GS_Q3	640	4.49	1.287	.0509
EF_GS_Q4	640	3.89	1.108	.0438
EF_CP_Q1	640	5.13	1.291	.0510
EF_CP_Q2	640	4.34	1.160	.0459
EF_CP_Q3	640	5.47	1.241	.0491
EF_CP_Q4	640	4.59	1.152	.0456
HF_INN_Q1	640	4.86	.911	.0360
HF_INN_Q2	640	5.45	1.118	.0442
HF_INN_Q3	640	5.31	1.137	.0449
HF_PC_Q1	640	5.25	1.252	.0459
HF_PC_Q2	640	4.27	1.387	.0548
HF_PC_Q3	640	4.26	1.401	.0554
HF_EC_Q1	640	5.35	1.243	.0491
HF_EC_Q2	640	5.42	1.311	.0519
HF_EC_Q3	640	5.53	1.124	.0444
BF_LTK_Q1	640	5.22	1.256	.0497
BF_LTK_Q2	640	5.42	1.395	.0552
BF_LTK_Q3	640	4.50	1.367	.0541
BF_RU_Q1	640	5.37	1.298	.0513
BF_RU_Q2	640	5.45	1.117	.0442
AdInt_Q1	640	5.90	1.101	.0435
AdInt_Q2	640	5.47	1.060	.0419
AdInt_Q3	640	5.06	1.002	.0396
AdInt_Q4	640	5.60	1.104	.0436
Valid N (listwise)	640			

Appendix F: Normality Tests For the Scale Items (Skewness and Kurtosis)

Normality Tests For the Scale Items (Skewness and Kurtosis)

Item	N Statistic	Skewness Statistic	Kurtosis Statistic
TF_RA_Q1	640	-.040	-.225
TF_RA_Q2	640	-.705	.454
TF_RA_Q3	640	-.098	-.422
TF_RA_Q4	640	-.395	.170
TF_RA_Q5	640	-.281	-.469
TF_COM_Q1	640	-1.072	1.591
TF_COM_Q2	640	-.624	-.239
TF_COM_Q3	640	-.839	.253
TF_COM_Q4	640	-.173	-.024
TF_TRI_Q1	640	.520	-1.046
TF_TRI_Q2	640	.390	-.048
TF_TRI_Q3	640	.219	-.022
TF_TRI_Q4	640	.294	-.786
TF_OBS_Q1	640	-.288	-.462
TF_OBS_Q2	640	.106	-.063
TF_OBS_Q3	640	-.157	-.048
TF_OBS_Q4	640	-.078	-.191
TF_OBS_Q5	640	-.374	.096
TF_CPX_Q1	640	-.471	-.813
TF_CPX_Q2	640	-.083	-.047
TF_CPX_Q3	640	-.092	-.039
TF_CPX_Q4	640	-.467	-.184
OF_TMS_Q1	640	-.438	.115
OF_TMS_Q2	640	-.598	.062
OF_TMS_Q3	640	-.672	.237
OF_TMS_Q4	640	-.295	.601
OF_TMS_Q5	640	-.060	.094
OF_ORA_Q1	640	-.227	-.689
OF_ORA_Q2	640	.232	-.641
OF_ORA_Q3	640	-.062	.110
OF_ORA_Q4	640	-.060	-.244
OF_ORA_Q5	640	.074	-.304

OF_EMP_Q1	640	-.038	.019
OF_EMP_Q2	640	-.372	.355
OF_EMP_Q3	640	-.217	1.024
EF_GS_Q1	640	-.079	-.310
EF_GS_Q2	640	-.167	-.497
EF_GS_Q3	640	-.025	-.212
EF_GS_Q4	640	-.043	-.106
EF_CP_Q1	640	-.250	-.219
EF_CP_Q2	640	-.299	-.410
EF_CP_Q3	640	-.042	-.167
EF_CP_Q4	640	-.115	-.299
HF_INN_Q1	640	-.414	.138
HF_INN_Q2	640	-.192	-.143
HF_INN_Q3	640	-.139	-.274
HF_PC_Q1	640	-.052	-.356
HF_PC_Q2	640	-.127	-.430
HF_PC_Q3	640	-.069	-.241
HF_EC_Q1	640	-.378	1.532
HF_EC_Q2	640	-.062	-.190
HF_EC_Q3	640	-.115	.143
BF_LTK_Q1	640	-.060	-.213
BF_LTK_Q2	640	-.128	-.283
BF_LTK_Q3	640	-.348	-.287
BF_RU_Q1	640	-.057	.249
BF_RU_Q2	640	-1.062	.135
AdInt_Q1	640	-.092	-.164
AdInt_Q2	640	-.177	.107
AdInt_Q3	640	-.076	-.280
AdInt_Q4	640	-.109	.118
Valid N (listwise)	640		

Appendix G: Z-score Results For the Scale Items

Z-score Results For the Scale Items

	N Statistic	Minimum Statistic	Maximum Statistic
Zscore(TF_RA_Q1)	640	-3.46339	1.71854
Zscore(TF_RA_Q2)	640	-3.17580	1.57306
Zscore(TF_RA_Q3)	640	-3.22441	1.58870
Zscore(TF_RA_Q4)	640	-3.34806	1.36387
Zscore(TF_RA_Q5)	640	-2.61354	1.54112
Zscore(TF_COM_Q1)	640	-3.22843	1.92417
Zscore(TF_COM_Q2)	640	-3.12012	2.19072
Zscore(TF_COM_Q3)	640	-2.99572	1.27173
Zscore(TF_COM_Q4)	640	-2.83312	2.19888
Zscore(TF_TRI_Q1)	640	-2.03481	2.34259
Zscore(TF_TRI_Q2)	640	-2.58699	1.48048
Zscore(TF_TRI_Q3)	640	-2.83931	1.43495
Zscore(TF_TRI_Q4)	640	-2.97802	2.78415
Zscore(TF_OBS_Q1)	640	-2.01561	1.48706
Zscore(TF_OBS_Q2)	640	-3.30861	1.68440
Zscore(TF_OBS_Q3)	640	-2.81844	1.57226
Zscore(TF_OBS_Q4)	640	-2.41791	1.74753
Zscore(TF_OBS_Q5)	640	-3.42877	1.10422
Zscore(TF_CPX_Q1)	640	-2.86940	1.85146
Zscore(TF_CPX_Q2)	640	-2.52871	0.91690
Zscore(TF_CPX_Q3)	640	-2.55671	1.26897
Zscore(TF_CPX_Q4)	640	-2.49740	1.72170
Zscore(OF_TMS_Q1)	640	-3.18442	2.17882
Zscore(OF_TMS_Q2)	640	-2.06779	1.51193
Zscore(OF_TMS_Q3)	640	-2.93639	1.60735
Zscore(OF_TMS_Q4)	640	-2.92489	2.02207
Zscore(OF_TMS_Q5)	640	-2.98702	2.14918
Zscore(OF_ORA_Q1)	640	-2.22680	2.18271
Zscore(OF_ORA_Q2)	640	-2.56312	2.91705
Zscore(OF_ORA_Q3)	640	-3.13307	1.26796
Zscore(OF_ORA_Q4)	640	-3.17993	1.01389
Zscore(OF_ORA_Q5)	640	-2.91015	2.04594

Zscore(OF_EMP_Q1)	640	-3.23990	1.13746
Zscore(OF_EMP_Q2)	640	-3.03436	1.71378
Zscore(OF_EMP_Q3)	640	-2.60336	1.29653
Zscore(EF_GS_Q1)	640	-2.69551	1.96352
Zscore(EF_GS_Q2)	640	-2.17731	2.20871
Zscore(EF_GS_Q3)	640	-1.93592	1.95056
Zscore(EF_GS_Q4)	640	-2.61097	2.80543
Zscore(EF_CP_Q1)	640	-2.42300	1.44805
Zscore(EF_CP_Q2)	640	-2.88362	2.29310
Zscore(EF_CP_Q3)	640	-2.79919	1.23375
Zscore(EF_CP_Q4)	640	-3.11853	2.09166
Zscore(HF_INN_Q1)	640	-3.13777	2.35204
Zscore(HF_INN_Q2)	640	-3.08550	1.38692
Zscore(HF_INN_Q3)	640	-2.91160	1.48591
Zscore(HF_PC_Q1)	640	-2.59504	1.39776
Zscore(HF_PC_Q2)	640	-2.35488	1.97179
Zscore(HF_PC_Q3)	640	-2.32842	1.95357
Zscore(HF_EC_Q1)	640	-3.50107	1.32791
Zscore(HF_EC_Q2)	640	-2.60761	1.20657
Zscore(HF_EC_Q3)	640	-3.14661	1.31650
Zscore(BF_LTK_Q1)	640	-2.56824	1.42988
Zscore(BF_LTK_Q2)	640	-2.45803	1.13569
Zscore(BF_LTK_Q3)	640	-2.55931	1.83004
Zscore(BF_RU_Q1)	640	-2.59487	1.25652
Zscore(BF_RU_Q2)	640	-2.75145	0.95967
Zscore(AdInt_Q1)	640	-2.63559	0.99919
Zscore(AdInt_Q2)	640	-3.27735	1.44245
Zscore(AdInt_Q3)	640	-3.04916	1.93924
Zscore(AdInt_Q4)	640	-3.26315	1.26744
Valid N (listwise)	640		