Quality 4.0 Adoption and Corporate Sustainability Performance in Malaysian Manufacturing Companies

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DECLARATION

I hereby declare that the work presented in this dissertation was conducted in full compliance with the regulations of Universiti Malaysia Sarawak (UNIMAS). Except where proper acknowledgment is given, this work is solely the effort of the author. This dissertation has not been accepted for the award of any other degree and is not being **concurrently** submitted for any other academic qualification.

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ABSTRACT

Quality 4.0, an advanced quality management paradigm driven by Industry 4.0 technologies, is emerging as a crucial factor in enhancing corporate sustainability within the manufacturing sector. This research explores the adoption of Quality 4.0, and its impact on corporate sustainability performance in Malaysian manufacturing companies. Anchored in the Technology-Organisation-Environment (TOE) framework and Resource-Based View (RBV) theory, a cross section quantitative survey was conducted and analysed with PLS-SEM. Results concluded with four positive and significant key adoption factors which include relative advantage, top management support, organisational culture and market pressure while AI compatibility, transformational leadership, and external support do not exhibit direct positive and significant effects. Quality 4.0 adoption is strongly and positively related to corporate sustainability performance across all three pillars (economic, environmental, and social). The study contributes by applying TOE framework for a Quality 4.0 adoption context in an emerging manufacturing economy and by positioning Quality 4.0 adoption as a strategic capability consistent with RBV that delivers corporate sustainability benefits. Practically, managers should demonstrate clear value cases, secure top management sponsorship, cultivate a supportive digital quality transformation culture, and leverage market pressure to overcome inertia. These priorities align with Malaysia's national push for digital transformation and AI adoption. Limitations include the cross-sectional design, self-reported measures, and a focus on medium and large manufacturing companies. Future research could employ longitudinal or mixed methods, multiple informants, and adoption-maturity perspectives. In essence, the study clarifies how and why Quality 4.0 adoption enhances corporate sustainability performance in Malaysian manufacturing companies.

Keywords: *Quality 4.0, Corporate Sustainability Performance, Industry 4.0, Total Quality Management, Manufacturing*

Adopsi Kualiti 4.0 dan Prestasi Kemampanan Korporat dalam Syarikat Pembuatan di Malaysia

ABSTRAK

Kualiti 4.0, paradigma pengurusan kualiti termaju yang dipacu oleh teknologi Industri 4.0, muncul sebagai faktor penting dalam meningkatkan kemampanan korporat dalam sektor pembuatan. Penyelidikan ini meneroka adopsi Kualiti 4.0, dan kesannya terhadap prestasi kemampanan korporat dalam syarikat pembuatan Malaysia. Berlabuh dalam rangka kerja Teknologi-Organisasi-Persekitaran (TOE) dan teori Pandangan Berasaskan Sumber (RBV), tinjauan kuantitatif keratan rentas telah dijalankan dan dianalisis dengan PLS-SEM. Keputusan disimpulkan dengan empat faktor adopsi utama yang positif dan signifikan termasuk kelebihan relatif, sokongan pengurusan atasan, budaya organisasi dan tekanan pasaran manakala keserasian AI, kepimpinan transformasi dan sokongan luaran tidak menunjukkan kesan positif dan ketara secara langsung. Adopsi Kualiti 4.0 berkait kuat dan positif dengan prestasi kemampanan korporat merentas ketiga-tiga tunjang (ekonomi, alam sekitar dan sosial). Kajian ini menyumbang dengan mengaplikasikan rangka kerja TOE untuk konteks adopsi Kualiti 4.0 dalam ekonomi pembuatan yang sedang pesat membangun dan dengan meletakkan adopsi Kualiti 4.0 sebagai keupayaan strategik yang konsisten dengan RBV yang memberikan manfaat kemampanan korporat. Secara praktikal, pengurus harus menunjukkan kes nilai yang jelas, mendapatkan penajaan pengurusan tertinggi, memupuk budaya transformasi kualiti digital yang menyokong dan memanfaatkan tekanan pasaran untuk mengatasi inersia. Keutamaan ini sejajar dengan dorongan nasional Malaysia untuk transformasi digital dan adopsi AI. Had termasuk reka bentuk keratan rentas, langkah yang dilaporkan sendiri dan tumpuan pada syarikat pembuatan sederhana dan besar. Penyelidikan masa depan boleh menggunakan kaedah membujur atau bercampur, berbilang informan, dan perspektif adopsi-kematangan. Pada dasarnya, kajian ini menjelaskan bagaimana dan mengapa adopsi Kualiti 4.0 meningkatkan prestasi kemampanan korporat dalam syarikat pembuatan Malaysia.

Kata Kunci: *Kualiti 4.0, Prestasi Kemampanan Korporat, Industri 4.0, Pengurusan Kualiti Menyeluruh, Pembuatan*

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LIST OF ABBREVIATIONS

4IR	Fourth Industrial Revolution
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AR	Augmented Reality
ASQ	American Society for Quality
AVE	Average Variance Extracted
BCG	Boston Consulting Group
CAGR	Compound Annual Growth Rate
CFA	Confirmatory Factor Analysis
CMV	Common Method Variance
CQI	Chartered Quality Institute
CRM	Customer Relationship Management
CSR	Corporate Social Responsibility
DBA	Doctor of Business Administration
DGQ	Deutsche Gesellschaft für Qualität
DOI	Diffusion of Innovations
EHS	Environment, Health and Safety
EIS	External Implementation Support
FVIF	Full collinearity variance inflation factor
GAI	Generative Artificial Intelligence
GDP	Gross Domestic Product
HQ	Headquarters
HTMT	Heterotrait-Monotrait Ratio of Correlations
I4.0	Industrial 4.0
IQM	Institute of Quality Malaysia
IoT	Internet of Things
ISO/TC	International Organisation for Standardisation/Technical Committee
IT	Information Technology
MES	Manufacturing Execution Systems
MIDA	Malaysian Investment Development Authority
MITI	Ministry of Investment, Trade and Industry
MNC	Multinational Corporation
MSME	Miro, Small, Medium Enterprise
NIMP	New Industrial Master Plan

PCDS	Post Covid-19 Development Strategy
PDCA	Plan, Do, Check, Act
PLS	Partial Least Square
ROI	Return on Investment
Q4.0	Quality 4.0
QMS	Quality Management System
R&D	Research and Development
RBV	Resource-Based View
SEM	Structural Equation Modelling
SMEs	Small and Medium Size Enterprises
TBL	Triple Bottom Line
TOE	Technology-Organisation-Environment
TQM	Total Quality Management
UFLPA	Uyghur Forced Labour Prevention Act
UNIMAS	Universiti Malaysia Sarawak
VIF	Variance Inflation Factor
VR	Virtual Reality
VRIN	Valuable, Rare, Inimitable, and Non-substitutable
VRIO	Valuable, Rare, Inimitable, and Organised

CHAPTER 1:
INTRODUCTION

1.1 Background of Study

Sustainability is essential for an organisation's continuity and long-term survival. In a business context, it is known as "corporate sustainability", which involves integrating long-term economic, environmental, and social considerations into a company's management and operations (Can, 2023). High quality is considered one of the competitive advantages to stand out and success in global market towards corporate sustainability. However, traditional quality philosophies have plateaued, entering stagnation with limited innovation to keep pace with manufacturing industry, and lose its leadership position in companies (Zonnenshain & Kenett, 2020).

Numerous researchers have recognised Total Quality Management (TQM) as key strategy for enhancing corporate sustainability performance (Abbas, 2020; Aichouni et al., 2024; AlShehail et al., 2022; Saha et al., 2022; Wassan et al., 2022). However, TQM was developed for relatively stable and low velocity operational environments, similar to other traditional quality philosophies. As a result, it has become increasing evident that TQM faces limitations in coping with the demands of digitalised operations such as those found in smart manufacturing. Advanced manufacturing processes generate large volumes of high frequency and multi-source data from interconnected systems, which exceed the analytical capacity of conventional sampling-based tools such as statistical process control and periodic audits (Escobar et al., 2021).

Furthermore, traditional quality approaches typically rely on delayed feedback loops and human-centered review cycles, restricting their ability to support real time quality monitoring and rapid corrective action in digitally connected manufacturing environments (Javaid et al., 2021). Quality data are also frequently fragmented across multiple platforms, including Quality Management System (QMS), Manufacturing Execution Systems (MES), IoT system, and external networks along the value chain. Hence, it creates data integrity and traceability challenges that traditional document-centric quality management systems struggle to address (Bernardo et al., 2024).

Since TQM plays a crucial role in sustainable development, efforts need to be extended by including Quality 4.0 in TQM (Aichouni et al., 2024; Nenadál et al., 2022), supporting the need of positioning Quality 4.0 as modern evolution of TQM, capable of addressing the complexity, speed, and data intensive nature of the digital era.

Germany introduced Industry 4.0 in 2011 as a strategic initiative to revolutionise its manufacturing sector by boosting competitiveness. This shift paved the way for Quality 4.0, a modern evolution of traditional quality management that seamlessly integrates into digital era. It will focus on achieving performance excellence amid rapid digital transformation accelerated by the post Covid-19 era (Oliveira et al., 2025).

Although the term Quality 4.0 was only recently shaped by a researcher, Dan Jacob from LNS Research in 2017, it has gained numerous discussions among researchers and practitioners (Antony et al., 2024; Antony, Sony, et al., 2023; Jacob, 2017a, 2017b; Mahin et al., 2024). It can be generalised as the enhanced version of TQM and organisational excellence within the context of Industrial 4.0 (I4.0) or the implementation of I4.0 technologies to quality management to empower business innovation, performance, efficiencies, and state of the art business models construction (Oliveira et al., 2025; Sony et al., 2020). Quality 4.0 has brought new insights to quality professionals to resume the leading force in organisational excellence (Antony, Swarnakar, et al., 2023; Oliveira et al., 2025; Zonnenshain & Kenett, 2020).

In a nutshell, the growing reliance on digital transformation in industries has made the integration of Quality 4.0 into corporate sustainability not just an option but will soon become a necessity. Traditional quality management approaches like TQM are struggling to keep up, hence making way for a more data-driven, technology-enabled approach to seek breakthrough in quality management. Quality 4.0 brings opportunities for innovation, efficiency, and resilience, but its adoption requires a shift in leadership, skills, and infrastructure. Beyond improving business performance, its potential to drive corporate sustainability remains an area for further exploration. To stay competitive, companies are urged to strategically align Quality 4.0 with their long-term corporate sustainability goals.

1.1.1 The Malaysian Scenario

The progression of the industry 4.0 concept into Malaysia context officially takes place with the announcement of Malaysia's National Fourth Industrial Revolution (4IR) Policy in 2021. The policy aims to advocate the use of technology to improve local capabilities including manufacturing sector by 30% productivity improvement within 10 years' time compared to 2020 (Economic Planning Unit, 2021; Shazrie, 2024). Industry 4.0 has indeed unleashed the prospects of technological capabilities and quantum leaps in almost every aspect of modern life including a paradigm shift in Total Quality Management (TQM).

The year 2020 proved to be a challenging one for Malaysia economy, as the advancement of the Covid-19 virus globally caused significant disruptions. Despite this unprecedented pandemic, it has accelerated the growth of digitalisation across various sectors including the manufacturing sector. At the national level, this acceleration reinforced the urgency of Industry 4.0 adoption and digital transformation as key mechanisms for economic resilience and recovery.

While national policies such as the National 4IR policy and subsequent new industrial master plans provide overarching strategic direction, implementation occurs unevenly across states and sectors. In this regard, Sarawak represents a leading example of how Malaysia's national digitalisation and Industry 4.0 aspirations are operationalised at the state level through targeted strategies and sectoral prioritisation. Sarawak state government has positioned itself at the forefront of digital transformation with its innovative strategies. In 2021, Sarawak proactively introduced the Post Covid-19 Development Strategy 2030 (PCDS2030) to drive comprehensive transformation by capitalising on global mega trends such as the new industrial revolution to strengthen its economic and social resilience following the pandemic (Economic Planning Unit Sarawak, 2021, 2024).

To help realise the objectives outlined in the PCDS 2030, one of the six dominant sectors which has been identified to lead economic growth is the manufacturing sector. As the second biggest driver to the Sarawak GDP, the manufacturing sector is expected to become a vital part in achieving the government's target of 30% GDP contribution by 2030, a target that mirrors the strategic importance of manufacturing sector within Malaysia's broader national development agenda (Economic Planning Unit Sarawak, 2021, 2024).

In addition, this sector is projected to provide the largest number of job opportunities, with an estimated 58, 000 jobs by 2030 (Economic Planning Unit Sarawak, 2021). To facilitate the growth of the six identified economic sectors, the Sarawak Government has identified seven enablers, one of which is Digital Transformation. This emphasis on digital transformation aligns closely with national Industry 4.0 priorities, with a target of achieving 70% SME adoption of digital platforms in Sarawak. Digital Transformation serves as a key enabler in advancing and strengthening the identified economic sectors (Economic Planning Unit Sarawak, 2021). This underscores the Sarawak Government's commitment to leveraging technology and innovation as catalysts for competitiveness and economic growth (Economic Planning Unit Sarawak, 2021, 2024).

Fast forward to 2023, after Malaysia welcomed its new government in November 2022, Malaysia Madani concept was launched as national policy in January 2023, aiming to foster good governance, sustainable development and racial harmony (Bernama, 2023). Various new road maps, policies and masterplans have been developed following the announcement of the new national policy, which include New Industrial Master Plan (NIMP) 2030. NIMP 2030 is a seven-year industrial policy designed to drive growth in manufacturing and related service sectors, aiming to increase the sector's value-added contribution to GDP by 61%, which is from RM364.1 million in 2022 to RM587.5 billion in 2030 (MITI, 2023). If successfully implemented, the plan anticipates a compound annual growth rate (CAGR) of 6.5% (MITI, 2023). Four missions have been devised, and Mission 2 is designed to advance the country towards becoming a digitally vibrant nation by embracing technology and digitalisation. Consequently, it will help to stimulate innovation, increase productivity and generate new opportunities for economic growth. Advanced automation and robotics, artificial intelligence, cloud computing and additive manufacturing are key areas to drive digitalization in manufacturing sectors. In October 2024, Ministry of Investment, Trade and Industry (MITI) announced a positive outlook on digital investments, highlighting a steady upward trend under Mission 2 of NIMP 2030. Malaysia has attracted RM185 billion in approved investments between 2021 and the second quarter of 2024 (Bernama, 2024b). These investments have created over 64,000 job opportunities, reinforcing the country's commitment in driving digital transformation and economic growth (Bernama, 2024b).

Along with NIMP 2030, Malaysia National Artificial Intelligence Road Map 2021-2025 announced in April 2021 will continue to compliment the realisation of this new masterplan (MOSTI, 2021). This policy commitment is further reinforced by the proposed National AI Technology Action Plan 2026-2030, which signals continuity in Malaysia's long term strategic direction for AI development and deployment beyond the current roadmap period (As, 2025). Emphasising the development of artificial intelligence (AI), particularly generative AI (GAI) is important because scholars have extensively explored its vast potential in various areas. Among them include predictive maintenance, product design enhancement, workforce skill development, quality assurance and quality control, market strategy optimisation, and demand projection in manufacturing processes (Doanh et al., 2023). As of third quarter of 2024, Malaysia had achieved 63% completion of Malaysia National Artificial Intelligence Road Map 2021-2025, demonstrating the country's commitment in advancing its Artificial Intelligence strategy (Bernama, 2024a). Oxford Insights has published a Government AI Readiness Index, where the country's effort in progressing AI adoption can be measured. Based on the report recently published in 2024, Malaysia was ranked 23rd in 2023, compared to its ranking of 29th in 2022, an improvement observed reflecting effective roll out of AI-related policies and initiatives (Bernama, 2024a).

The acceleration of high impact national strategies including the National Semiconductor Strategy (Lee & Liew, 2024) and the Thirteenth Malaysia Plan (RMK-13, 2026-2030) (Bernama, 2025b) introduces a heightened sense of urgency for Malaysian manufacturing companies to move beyond policy awareness towards effective implementation. These strategies place advanced manufacturing, digital resilience, and high value industrial upgrading at the center of Malaysia's economic transformation agenda. In this context, Quality 4.0 adoption should be understood not merely as technological upgrade, but as a strategic capability that enables manufacturing companies to operationalise digital driven quality management, align with national digital ambitions, and remain competitive within increasingly complex and data intensive manufacturing ecosystems.

Collectively, these national and state-level developments provide important contextual grounding for understanding the accelerating adoption of Industry 4.0 technologies and their implications for quality management practices within Malaysia's manufacturing companies, which remains the central focus of this research.

1.1.2 Manufacturing Industry

Manufacturing sector has been put under the spotlight of corporate sustainability despite it is one of the primary industries driving significant economic growth and development in a country. The world has been producing seven times more goods than it did when compared between late 1980 and 1950 and is expected to grow five to tenfold based on projected population growth rates (WCED, 1987). Traditional manufacturing systems have unfavourable reputations when comes to meeting the Tripple Bottom Line (TBL) of sustainable development (Jayashree et al., 2022). Numerous stakeholders such as the public, government, and non-governmental agencies have put pressure on companies to improve corporate sustainability.

As a result, manufacturing sector is one of the early adopters to embrace the compounding advantages of Quality 4.0 and are in transition phase entering this latest paradigm to boost the output and quality of the final products towards lowering negative impact in the aspect of corporate sustainability. Scholars have suggested the utilization of Quality 4.0 as salient techniques to improve the corporate sustainability performance (Antony, Sony, et al., 2022; Antony, Swarnakar, et al., 2023; Saha et al., 2022).

Comparing the same period in 2023, Malaysia's manufacturing sector observed a 4.7% growth in its contribution to the GDP in the second quarter of 2024, rising by RM4.2 billion (Bernama, 2024b). Employment in the manufacturing sector also improved by 0.9%, adding 200, 000 jobs because of the NIMP's implementation (Bernama, 2024b). In addition, under NIMP 2030, Malaysia also aims to transition at least 3,000 manufacturing facilities to smart factories by 2030 (Bernama, 2024b). Malaysian Investment Development Authority (MIDA) is tasked to manage an intervention fund to support this shift. To date, close to 500 companies have tapped into the intervention fund (Bernama, 2025a). As a leading state in digital transformation and economic development, Sarawak government positions its manufacturing sector as a key driver to drive the economy of the state, as outlined in PCDS 2030. According to the latest data from Economic Planning Unit Sarawak in 2024, the sector contributed an average of 27.5% to Sarawak's GDP between 2021 and 2023. Sarawak has attracted a total of RM82.6 billion in investments, with the manufacturing sector securing RM21.5 billion (Economic Planning Unit Sarawak, 2024). Over 11, 000 jobs were created, particularly in electrical and electronic (E&E) products, chemicals, and basic metal products (Economic Planning Unit Sarawak, 2024).

Malaysia's push for digital transformation through policies such as 4IR Policy and NIMP 2030 highlights its commitment to integrate advanced technologies into manufacturing industry. With AI adoption accelerating under the Malaysia National Artificial Intelligence Roadmap, the manufacturing industry is well-positioned to embrace Quality 4.0 and corporate sustainability. The focus on AI-driven predictive maintenance, quality assurance, and process optimisation aligns with the goals of corporate sustainability performance, helping Malaysian manufacturing companies to reduce waste, optimise resources, and improve long-term competitiveness. However, the challenge lies in how well local manufacturing companies, especially the medium and large manufacturing companies as potential early adopters of Quality 4.0 can adapt to and leverage these advancements across enterprise-wise systems, manage significant capital investments in advanced digital infrastructure, and align organisational structures and legacy process with data driven decision making (Fadilasari et al., 2024). While the government's policies provide a strong foundation, success will depend highly on industry-wide adoption, firm's strategic readiness, leadership commitment, workforce upskilling at scale, and the ability to translate technological investments into measurable corporate sustainability performance outcome. If implemented effectively, Malaysia's embrace of Quality 4.0 could position its manufacturing industry as a regional leader in sustainable, tech-driven industrial growth.

In summary, Quality 4.0 adoption in Malaysian manufacturing companies is expected to propel to the next level with the empowerment from Malaysia Government under the umbrella of New Industrial Master Plan (NIMP) 2030 and Malaysia National Artificial Intelligence (AI) Road Map 2021-2025, which are also the enablers of Quality 4.0 adoption and via the establishment of digital economy ecosystem creation.

1.2 Problem Statements

In 2019, BCG collaborated with Deutsche Gesellschaft für Qualität (DGQ) and ASQ in an industry survey. The study revealed that manufacturing and R&D sectors acknowledged the importance of Quality 4.0 and its potential advantages for digital transformation in quality management. However, the adoption level was surprisingly lower than expected with only 16% adoption from the early adopters based in Europe, primarily in Germany, the inception place of Industry 4.0 (Küpper et al., 2019). Despite nearly 67% of survey participants believing Quality 4.0 would significantly impact their operations within five years, most companies have yet to begin its implementation. Insufficient support from senior management, ambiguous digital strategy, lack of digital skills, absence of quality culture, cybersecurity concerns, outdated systems, fragmentated quality data, data integrity issues, lack of funding, and organisational resistance are challenges faced impeding the implementation based on the survey (Küpper et al., 2019).

These challenges were further intensified by the Covid-19 pandemic, which disrupted global sustainability efforts (Sarker et al., 2021). Despite evolving quality management approaches, product recalls have risen, with 50% of respondents in 2024 survey from global quality professionals believing their organisations effectively managing quality, a potential misguided perception of quality success (ETQ Reliance, 2024). Quality 4.0 offers a promising role in bridging these gaps. However, according to Fadilasari et al. (2024), many companies across manufacturing-oriented companies such as material and metal, engineering and construction, IT and communication, automotive, food and beverages, and chemicals globally reported persistent reliance on traditional quality systems and maintained a status quo due to challenges such as lack of management support, poor organisational structure, financial issues, resistance to change, and cybersecurity concerns. Within medium and large manufacturing companies, these challenges are compounded by the complexity of integrating Quality 4.0 adoption with extensive legacy systems, multi-layered governance structures, and geographically dispersed operations. In such contexts, management support and financial constraints often reflect difficulties in prioritising and justifying large-scale, high ROI digital quality initiatives, while resistance to change is reinforced by entrenched processes, corporate inertia, and heightened data governance and cybersecurity requirements (Fadilasari et al., 2024).

In addition, Malaysian manufacturing companies face significant challenges in achieving corporate sustainability. Economically, manufacturing sector struggles with global uncertainties, supply chain disruptions, and a weakening ringgit, impacting growth and competitiveness (MIDA, 2024). Recent closures of several manufacturing plants vividly illustrated the difficult operating environment and its impact on economic sustainability of manufacturing companies in Malaysia (Harun & Sallehuddin, 2024; Latiff, 2024; Nair, 2025). In addition, the latest escalating US tariff of 19% on Malaysian exports came into effect in August 2025, with the potential for 100% tariffs on semiconductors, prompting a downward revision of growth forecast by Bank Negara Malaysia (Latiff, 2025). Economists remain cautious about trade prospects due to persistent global tariff uncertainty (Abu, 2025).

Environmentally, greenhouse gas emissions in Malaysia are primarily driven by the manufacturing, making it the second-largest contributor, accounting for 10% of the country's total emissions (MIDA, 2025). Efforts to adopt green technologies are hindered by financial constraints and outdated systems. Socially, the industry struggles with labour shortages, including a persistent skills gap and low paying jobs, heightened by Covid-19 pandemic and on geopolitical tensions (MIDA, 2024). Although corporate social responsibility (CSR) initiatives are vital, many businesses find them costly and complex to implement (Azman & Mustapha, 2018). The wave of factory closures further exposes pressing social sustainability challenges in Malaysia's manufacturing sector, where large scale job losses, wage disputes, and prolong human rights concerns continue affecting thousands of workers (Latiff, 2024; Nair, 2025; Zahiid, 2024).

Despite widespread adoption of traditional quality management systems and international standards such as ISO9001 certification (FMM, 2024), Malaysian manufacturing companies continue to face operational disruptions, declining competitiveness, factory closures, environmental pressures, and labour-related challenges indicating that current quality management approaches are insufficient to sustain corporate sustainability performance (Harun & Sallehuddin, 2024; Latiff, 2024; MIDA, 2024; Nair, 2025). While national initiatives have positioned digital transformation as a priority for Malaysian manufacturing companies (e.g. NIMP 2030), evidence suggest that Malaysian manufacturers are still at early or uneven levels of digital maturity with only 11% had transformed most processes by 2022 and 55% lack an integrated enterprise-wide digital transformation strategy (Ahmed et al., 2024). Under these conditions, quality management is likely to remain fragmented and only weakly connected to digital technologies, limiting its potential to support corporate sustainability performance enhancement (Ahmed et al., 2024).

To tackle these challenges, a holistic approach is needed to integrate three pillars of corporate sustainability, which cover economic, environmental and social sustainability with renewed quality management practices. Quality 4.0 has the potential to drive transformative improvements in corporate sustainability performance. However, Quality 4.0 is beyond technology, raising challenges for Total Quality Management (TQM) and corporate sustainability. There are still unexplored barriers which need to be addressed to achieve new optimum in innovation, performance, and operational excellence (Ghatak & Garza-Reyes, 2024; Sony et al., 2020). In addition, the adoption Quality 4.0 is still in its early stages, with limited success evidence and no known unified adoption and implementation framework (Alsadi et al., 2024; Antony et al., 2024; Sony et al., 2021). Limited research has scrutinised how the adoption of Quality 4.0 can impact corporate sustainability performance (Antony, Sony, et al., 2022; Antony, Swarnakar, et al., 2023), particularly under the umbrella of the Triple Bottom Line (TBL) framework.

This research gap is particularly critical in the Malaysian manufacturing context, where ambitious national policy initiatives such as the NIMP 2030, National AI Technology Action Plan 2026-2030, National Semiconductor Strategy and the Thirteenth Malaysia Plan (RMK-13, 2026-2030) explicitly promote advanced digitalisation, corporate sustainability, and quality-led competitiveness. Despite these strong policy imperatives, there remains limited empirical evidence to guide Malaysian manufacturing companies on how Quality 4.0 adoption can effectively translate policy aspirations into measurable corporate sustainability outcomes. The absence of such evidence constrains informed decision making at both company and policy levels, thereby elevating the urgency for empirical investigation into the role of Quality 4.0 in advancing TBL performance within Malaysian manufacturing companies.

In conclusion, gathering empirical data is crucial for gaining insights into Quality 4.0 adoption, its impact on quality management, as well as its contribution to corporate sustainability performance in the Malaysian manufacturing companies. This approach will add value to the domestic market and ensure quality management remains relevant to its historical impact on corporate sustainability.

1.3 Objectives of Study

The understanding of Quality 4.0 adoption framework is a prerequisite and a crucial element for Malaysia manufacturing sector before resource allocation into Quality 4.0 implementation and subsequently bring positive impacts to corporate sustainability performance.

1.3.1 General Objective

This research generally aims to address key research gaps identified in Section 1.2 by examining factors influencing Quality 4.0 adoption and its impact on corporate sustainability performance in Malaysia's manufacturing sector. Grounded in the Technology-Organisation-Environment (TOE) framework, the study evaluates seven key factors: relative advantage, artificial intelligence (AI) compatibility, top management support, transformational leadership, organisational culture, external support, and market pressure on Quality 4.0 adoption. Additionally, this research assesses how Quality 4.0 adoption impacts corporate sustainability performance, aligning with the Triple Bottom Line (TBL) of sustainable business development.

1.3.2 Specific Objectives

In addition to the above-mentioned general objectives, this research will focus on four specific objectives, which include:

i. To determine the impact of technological context (i.e., relative advantage and artificial intelligence compatibility) on Quality 4.0 adoption in Malaysian manufacturing companies.

ii. To examine the impact of organisational context (i.e., top management support, transformational leadership, and organisational culture) on Quality 4.0 adoption in Malaysian manufacturing companies.

iii. To investigate the impact of environmental context (i.e., external support and market pressure) on Quality 4.0 adoption in Malaysian manufacturing companies.

iv. To evaluate the effect of Quality 4.0 adoption on corporate sustainability performance (i.e., economic, social and environmental aspects) in Malaysian manufacturing companies.

1.4 Research Questions

This study will strive to address the four research questions which include:

i. Do technological context dimensions such as relative advantage and artificial intelligence compatibility affect Quality 4.0 adoption in Malaysian manufacturing companies?

ii. Do organisational context dimensions such as top management support, transformational leadership, and organisational culture affect Quality 4.0 adoption in Malaysian manufacturing companies?

iii. Do environmental context dimensions such as external support and market pressure affect Quality 4.0 adoption in Malaysian manufacturing companies?

iv. Does Quality 4.0 adoption affect corporate sustainability performance in terms of economic, social and environmental aspects?

1.5 Definitions of Key Terms

The key dimensions of the integrated TOE framework and their relationship with the adoption of Quality 4.0, along with the subsequent impact on corporate sustainability performance within Malaysia's manufacturing sector will be examined in this research. Below is a summary of the key terms and their definitions as applied in this research:

i. **Quality 4.0**: The application of Industry 4.0's advanced digital technologies to enhance traditional best practices in quality management (Küpper et al., 2019).

ii. **Adoption:** A decision to make full use of an innovation as the best course of action available (Rogers, 2003).

iii. **Relative Advantage:** The degree to which an innovation is perceived as better than the idea it supersedes (Rogers, 2003).

iv. **Compatibility:** The degree to which an innovation aligns with existing technology structure, infrastructure and procedures, values and norms, experiences, and the information sharing needs of the potential adopters (Awa et al., 2017; Rogers, 2003; Teo & Pian, 2003).

v. **Top Management Support:** When a senior management project sponsor/champion, the CEO and other senior managers devote time to review plans, follow up on results and facilitate management problems (Young & Jordan, 2008)

vi. **Transformational Leadership:** Transformational leadership involves inspiring followers to commit to a shared vision and goals for an organisation or unit, challenging them to be innovative problem solvers, and developing followers' leadership capacity via coaching, mentoring, and provision of both challenge and support (Bass & Riggio, 2006)

vii. **Organisational Culture:** The collective norms, beliefs, and values that are shared by the members of an organisation (Gimenez-Espin et al., 2013).

viii. **External Support:** The readiness of assistance for implementing and utilising a technology-based solution or innovations (Premkumar & Roberts, 1999).

ix. **Market Pressure:** The pressure experienced by organisations who feels that rivals, customers or suppliers are urging them to adopt innovations (Jayashree et al., 2022).

x. **Corporate Sustainability:** Meeting the needs of a firm's direct and indirect stakeholders (such as shareholders, employees, clients, pressure groups, communities etc.), without compromising its ability to meet the needs of future stakeholders as well (Dyllick & Hockerts, 2002).

xi. **Corporate Sustainability Performance:** The extent to which businesses take into account the economic, social, and environmental factors in their activities, and their effects on society and business (Özkan & Ağ, 2021).

xii. **Economic Sustainability:** Economically sustainable companies guarantee at any time cashflow sufficient to ensure liquidity while producing a persistent above average return to their shareholders (Dyllick & Hockerts, 2002).

xiii. **Environmental Sustainability:** Ecologically sustainable companies use only natural resources that are consumed at a rate below the natural reproduction, or at a rate below the development of substitutes. They do not cause emissions that accumulate in the environment at a rate beyond the capacity of the natural system to absorb and assimilate these emissions. Finally, they do not engage in activity that degrades eco-system services (Dyllick & Hockerts, 2002).

xiv. **Social Sustainability:** Socially sustainable companies add value to the communities within which they operate by increasing the human capital of individual partners as well as furthering the societal capital of these communities. They manage social capital in such a way that stakeholders can understand its motivations and can broadly agree with the company's value system (Dyllick & Hockerts, 2002).

1.6 Scope of Study

Theoretically, this research was bounded by the TOE framework for explaining Quality 4.0 adoption and the RBV theory for examining its contribution to corporate sustainability performance across triple bottom line dimensions.

Geographically, the research was conducted in Malaysia, covering thirteen states and one federal territory. The scope was limited to manufacturing companies registered under the Federation of Malaysian Manufacturers, which had adopted Quality 4.0 and with company size more than 75 employees (medium and large companies). This focus was appropriate because those companies were more likely to have the necessary technological readiness, organisational capacity, and resource availability to be Quality 4.0 early adopters, which is inherently a capital-intensive transformation within the manufacturing sector (Wawak et al., 2023).

Methodologically, the target respondents were senior level quality professionals such as Senior Quality Executive, Quality Manager, Senior Quality Manager, Quality Director etc. employed within the unit of an organisation that have knowledge of Quality 4.0 adoption and implementation. A quantitative survey questionnaire, using a cross-sectional research design, was utilised to capture a snapshot of Quality 4.0 adoption and its impact on corporate sustainability performance, supporting the generalisation of findings across Malaysian manufacturing companies.

1.7 Significance of Study

1.7.1 Theoretical Significance

By investigating and exploring the Quality 4.0 adoption and how it affects corporate sustainability performance, this study will contribute to the theoretical foundation of Quality 4.0 research. It expands the current literature by examining adoption factors that address gaps in previous studies, particularly in applying findings across different industries or geographical regions with similar adoption challenges. Eventually, the research interest can expand from a macro level perspective to a more micro level analysis, incorporating local contexts through a top-down approach for deeper insights and enrich theoretical understanding, and eventually advancing knowledge on how Quality 4.0 supports corporate sustainability performance and practices.

1.7.2 Practical Significance

On the practical side, the study will provide solid foundation to Malaysian manufacturing companies by helping them to accelerate their process either in the adoption or implementation phase with the aim to improve their corporate sustainability performance, By connecting Quality 4.0 adoption to improvements in corporate sustainability performance, the findings will support manufacturing companies in navigating current global challenges, such as post Covid-19 recovery, intensified geopolitical conflicts, and increasing global tariff uncertainty. The key takeaway from the research will provide insightful reference to policymakers, specifically government officials and regulatory authorities, administrators such as managers and department heads in manufacturing companies, and practitioners, namely industrial professionals, in developing countries like Malaysia, to establish suitable guidelines and standards during the Quality 4.0 realisation process. The goal is to obtain competitive advantage and increase their market presence towards Malaysia 5.0 vision under the backbone of 4IR policy and subsequently realising the vision of NIMP 2030. By putting their corporate sustainability practices into action, manufacturing companies will enjoy the benefit from increased investment in respect of every TBL dimension.

1.8 Chapter Summary

This research is proposed to explore the adoption of Quality 4.0 and the impact towards corporate sustainability performance in Malaysian manufacturing companies. In this chapter, it outlines the research background which consists of corporate sustainability issues, the emergence of Quality 4.0, and the current state of manufacturing sector towards corporate sustainability performance. It is followed by defining the problem statement which will disclose the gaps identified based on literature review and current business challenges, setting research objectives, and generating research questions. This chapter also summarises the scope of the study by clearly specifying the theoretical boundary, which is grounded in the TOE framework and RBV theory, followed by the geographical boundary, which is limited to FMM registered medium and large manufacturing companies operating in Malaysia and have adopted Quality 4.0, and lastly, the methodological boundary, which include senior level quality professionals as the target respondents and the use of a quantitative, cross sectional survey design. Finally, it emphasises the significance and motivation of the research on how it adds on to the current literature in corporate sustainability, quality management, and manufacturing sector in Malaysia. This chapter aims to generate a synopsis of the research to be conducted and provides direction on how they will contribute to the overall research.

CHAPTER 2:

LITERATURE REVIEWS

2.1 Introduction

Chapter 2 establishes the theoretical groundwork for this study, drawing from relevant scholarly research and domain-specific expertise. It is structured into several key sections, beginning with an exploration of the overarching research concepts and variables. It then identifies the foundational theories supporting the study, followed by the development of a conceptual framework that visually illustrates the variables and their interconnections. Finally, the chapter concludes with the formulation of research hypotheses. This chapter generates a comprehensive and in-depth explanation of the research problem. Meantime, it also puts forward insight in identifying the gaps and research opportunities.

2.2 Total Quality Management (TQM)

The concept of quality philosophy has evolved significantly, transitioning from an emphasis on quality inspection to the era of Total Quality Management (TQM). TQM is considered a comprehensive philosophy that integrates diverse fields, from quantitative and qualitative data analysis, behavioural science, process interpretation, and economic concepts to achieve continuous enhancement of all processes' quality (Furterer & Wood, 2021). Its methodology fits well with the concept of corporate sustainability and hence, it is not surprising that TQM is being adopted as one of the organisational excellence models to achieve corporate sustainability goals.

The eight fundamental elements of TQM have been condensed to incorporate the organisation's culture and operations with data, strategy, and fruitful communication of quality disciplines. Among those include total employee participation, customer centred, process focused, consolidated system, strategic and systematic methodology, communication, evidence-based decision making, and continual improvement (Furterer & Wood, 2021). Table 2-1 summarises five distinct strategies that may be utilized to develop TQM in the organisations.

Table 2-1:
TQM Development Strategies

Strategy	Description	Methodology
Strategy 1	The organisation model approach	Application of benchmarking to organisations that have taken leadership role in TQM and integrate the success factors into own organisation
Strategy 2	The TQM element Approach	Application of TQM element-by-element methodology that utilises TQM tools to embrace improvements
Strategy 3	The Japanese total quality approach	Application of Deming-Prize winning companies' strategies and integrate into organisation's culture and sustainability
Strategy 4	The guru approach	Application of writings and teachings to recognize deficiencies and provide remedies
Strategy 5	The award criteria approach	Application of quality award criteria as tools for improvement

Source: Furterer and Wood (2021)

Furterer and Wood (2021) establishes a generic model for effective TQM implementation which includes 12 elements as listed below:

- Executive management's commitment
- Quality Management System (QMS) assessment
- Communication of core values and principles
- TQM master plan
- Identification and prioritisation of customer demands
- Critical business process mapping
- Process improvement team's formation
- Steering committee's momentum
- Managerial individual commitment and contribution
- Daily process management and standardisation

- Regular progress evaluation
- Constant employee awareness

Success factors of implementing and developing TQM can be leveraged and normally it requires a unique integration of various adaptations to the existing business model. Integration of TQM and corporate sustainability is in tandem with the progression of the TQM implementation, and it yields positive impact to the businesses. The literature highlights how Total Quality Management (TQM) plays its significant role in enhancing corporate sustainability performance across various dimensions, including social, environmental, and economic aspects.

Tasleem et al. (2019) emphasised that TQM positively influenced corporate sustainability by streamlining operations and cultivating an environment for continual improvement. Similarly, Abbas (2020) explained how knowledge management mediated the link between TQM and corporate sustainability, suggesting that effective knowledge utilisation enhances the long-term benefits of quality initiatives. Saha et al. (2022) on the other hand found that TQM will provide substantial contribution to sustainable growth, when combined with Industry 4.0 advancements, particularly in the manufacturing sector. Their findings highlighted how TQM principles support the industry 4.0 technologies adoption, further bridging the gap among digital transformation and corporate sustainability. Furthermore, Wassan et al. (2022) reinforced the argument that TQM provides positive impact towards sustainable competitiveness in corporate sustainability performance. Collectively, these studies suggest that TQM remains a critical driver of corporate sustainability performance, particularly when aligned with emerging technologies. The incorporation of digital tools and smart manufacturing process amplifies TQM's impact, making a strategic enabler for long-term business sustainability and competitive advantage.

TQM enters a new paradigm when Industry 4.0 creates an advanced horizon in quality world which gives birth to Quality 4.0, an innovative concept that redefines the quality management landscape. In manufacturing sector, particularly in the backdrop of Industry 4.0, corporate sustainability and quality are intertwined concepts. Leveraging digital technologies enables companies to reduce their environmental impact and increase their resource efficiency and hence leads to more sustainable operations. Quality 4.0 on the other hand harnessing digital technologies to revamp product and service excellence, reducing defects and waste and moves towards increasing customer satisfaction. This in return can enhance customer loyalty, improve brand reputation, and ultimately, achieve corporate sustainability goals of the companies.

2.3 Quality 4.0 and Its Fundamentals

Before delving into the adoption of Quality 4.0, it is crucial to establish a fundamental understanding of its concept, key dimensions, and the tools emerging from Industry 4.0 advancements. This section presents an outline of its definition, understanding of its dimensional framework, and technological enablers, serving as a foundation for understanding its adoption and implementation.

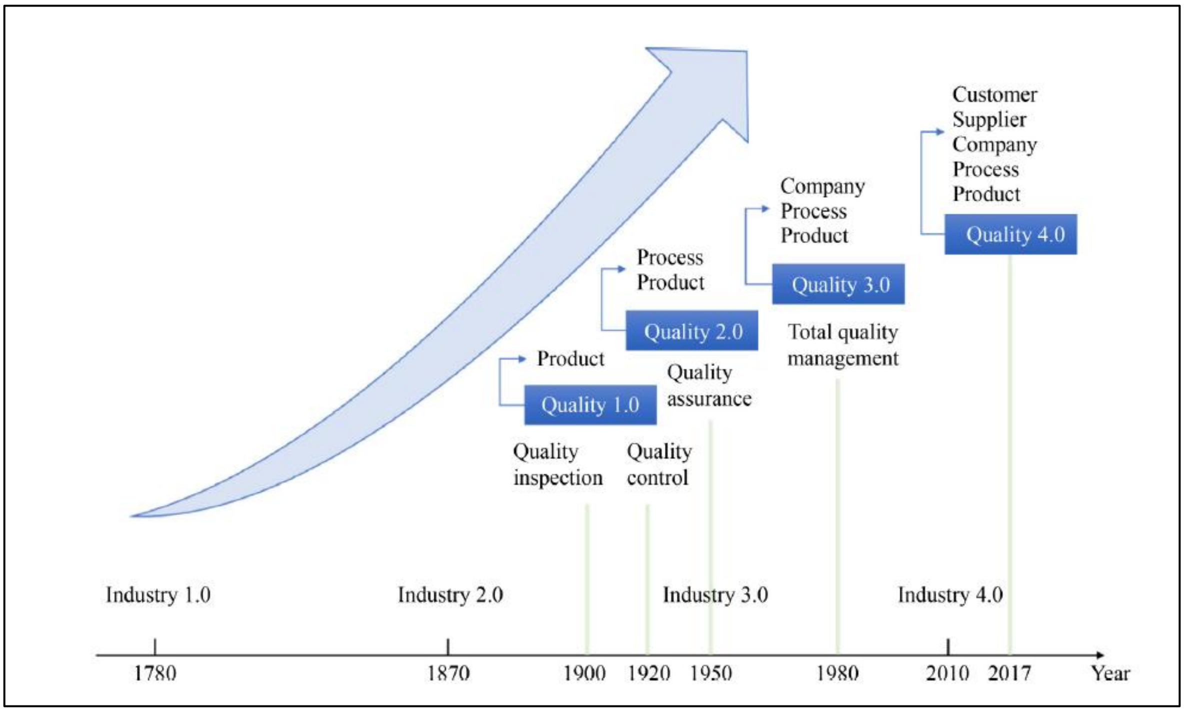
2.3.1 Quality 4.0 Definition

Quality 4.0 has entered our vocabulary in recent years. It is no longer a buzzword to the manufacturing sector when there are already whispers and murmurs of Quality 5.0 which are currently still in its most nascent stages. The concept of Quality 4.0 is brought up in 2017 by LNS research and although myriad definitions have been debated and discussed, returning to the origin of the concept and redefining Quality 4.0 would be a justifiable action. The utilisation of industrial transformation techniques along with cutting-edge digital technologies aims to revolutionise quality management and bring significant enhancements in the value-chain throughout product development, supplier management, operational processes, logistics, and customer engagement (Jacob, 2017a). It integrates technology, people, and processes to enable transformation and growth towards corporate sustainability (Jacob, 2017b).

A survey conducted by Küpper et al. (2019) manifested the status of Quality 4.0 adoption in developed countries. According to the report, Quality 4.0 refers to how digital technologies from Industry 4.0 are embedded into quality management practices, with technology being one component of a larger quality transformation. This definition also echoed with the research reported by Turner and Oakland (2021) under CQI research program in which their operating definition of Quality 4.0 is the fusion of technology and human resources to enhance an organisation's quality, its services, products, and the results it produces. Radziwill (2020) on the other hand emphasising connectedness, intelligence, and automation to achieve quality goals and amplify performance benefits utilising Industrial 4.0 approach.

Watson (2019) compared two development histories of Quality 4.0 and Industry 4.0. He created a table to illustrate the evolution of principles, methods, and tools over time by relating Quality 4.0 to Industry 4.0. The aligned approach presents an interactive relationship between industrial advancements and quality improvements. Similarly, Liu et al. (2023) also conducted a comparative analysis of their histories, providing a visualisation of how quality management philosophies have evolved alongside industrial revolution. Figure 2-1 illustrates the comparative analysis of both histories in a simplified manner.

Figure 2-1:
Evolution of Quality Management Philosophy



Source: Liu et al. (2023)

Apart from efforts from industry practitioners to conceptualise Quality 4.0 definition, the academic community has also substantially advanced this emerging domain of quality management research. Both communities shared the same goal to define Quality 4.0 in response to business needs. Consistent with practitioner's perspectives, technology is consistently recognised as the core element in defining Quality 4.0. Researchers have sought to establish a connection between technology, digital transformation, and quality (Antony, McDermott, et al., 2022; Chiarini, 2020; Chiarini & Kumar, 2022; Escobar et al., 2022; Maganga & Taifa, 2023; Oliveira et al., 2025; Sader et al., 2022; Sony et al., 2020; Sureshchandar, 2022; Thekkoote, 2022).

In recent studies, Dias et al. (2022) defined Quality 4.0 as the provision of exceptional quality through the integration of modern technology, strengthening the ability of both individuals and quality management tools. This definition emphasises the synergy between human expertise and technological advancements in ensuring quality improvement. Sader et al. (2022) expanded on this definition by describing Quality 4.0 as an extension of traditional quality management, where conventional quality practices are integrated with recent technologies. This integration broadens the scope of quality management while improving performance and efficiency. Similarly, Sureshchandar (2022) highlighted the digitalisation aspect of Quality 4.0, describing how it reshapes quality activities through Industry 4.0 technologies. This view enforces the idea that Quality 4.0 is primarily fuelled by technological innovations that enhance digital quality processes.

Thekkoote (2022) further elaborated on this concept by framing Quality 4.0 as the digital evolution of TQM, underscoring its implications for people, processes, and technology. This definition aligns with Maganga and Taifa (2023) perspective, which frame Quality 4.0 as an innovative quality management paradigm built upon Industry 4.0 technologies, highlighting the significance of digitalisation and system integration. Lastly, according to Oliveira et al. (2025), Quality 4.0 represents the next generation of quality management, attributing its emergence to the rapid technological advancement introduced in the fourth industrial revolution.

Overall, these studies illustrate a shared understanding that Quality 4.0 is a novel concept at its early phase of development and applications, which makes it rather challenging to be defined using a single definition. Generally, it is seen as blending digital technologies with traditional quality management methods, enhancing rather than replacing them. As part of Industrial 4.0 revolution, Quality 4.0 represents natural evolution, focusing on meeting customer needs via offering more personalised products and services through the digitalisation of processes and systems (Broday, 2022). Additionally, these definitions align in their emphasis on how important it is to adopt new technologies, and to appreciate the benefits acquired from the implementation (Saihi et al., 2023).

For this research, the operational definition of Quality 4.0 is adopted from Küpper et al. (2019) as leveraging Industry 4.0 technologies to improve established quality management best practices. When viewed collectively, the definitions of Quality 4.0 presented by both academic and industry scholars converge on a common emphasis on the integration of Industry 4.0 technologies with established quality management practices to enhance organizational performance. In this regard, the definition proposed by Küpper et al. (2019) effectively synthesise the core elements articulated across the literature. It captures the essence of Quality 4.0, embedding digital transformation with recognised principles in quality management. It aligns with both industry and academic perspectives, emphasising technology as a key enabler rather than a replacement for traditional quality management. Furthermore, it gives a clear and practical framework for analysing the integration of digital tools in quality processes, making it particularly suitable for the context of Malaysian medium and large manufacturing companies, where Quality 4.0 adoption is typically pursued through incremental digital transformation of mature quality system within complex operational and legacy infrastructures. It is also promoted under Malaysia's industrial policies and provides a pragmatic and conceptually coherent foundation for analysing Quality 4.0 adoption and its implication to corporate sustainability performance in this research.

2.3.2 Quality 4.0 Dimensions

Quality 4.0 has progressed to the point where researchers recognised that Quality 4.0 is not just a single definition, but could be expanded to a multi-dimensional framework, with the aim to better capture the essence of Quality 4.0. LNS research as the pioneer in building Quality 4.0 strategy handbook has established eleven facets of Quality 4.0 in which organisations can utilize to learn, strategize and to execute which include app development, analytics, collaboration, data, competency, leadership, compliance, culture, connectivity, management system, and scalability under the three big umbrellas of people, process, and technology (Jacob, 2017a). Conventional quality methodologies such as TQM are not supplanted by Quality 4.0. Instead, it strengthens and upgrades them. Manufacturers can leverage this framework to assess their current position and determine the necessary adjustment to transition towards a future state.

Dias et al. (2022) tried to create a connection between technology and quality, laying the foundation for Quality 4.0, which revolves around people, processes and technology. Technology is regarded as the most dominant dimension in literature, although the contribution is not concordant. Thus, the authors have put forward their interpretation of Quality 4.0 as the attainment of higher quality standards by leveraging advanced technology to enhance the abilities of individuals, process improvement tools, thereby augmenting the achievements of traditional quality measures.

Chiarini and Kumar (2022) on the other hand also followed the similar meta framework of using People-Process-Technology dimensions as an attempt to formulate Quality 4.0 model. Kumar et al. (2022) resonated the perspectives of Chiarini and Kumar (2022) in their review of Quality 4.0, adopting similar sub-dimensions, as part of an additional effort to conceptualise Quality 4.0 within a multi-dimensional framework.

Sureshchandar (2022) and Sureshchandar (2023) expanded on the multi-dimensional concept of Quality 4.0 by using confirmatory factor analysis (CFA) and analytic hierarchy process (AHP) in their empirical studies, contributing to the development of Quality 4.0 theory through the exploration of its twelve dimensions, namely strategic leadership, quality culture, customer centricity, quality management system, competence, analytical thinking, metrics and data-driven decision making, advanced analytics, data governance, innovation, and new-age technological tools. In addition, Prashar (2023) applied morphological analysis to delve into quality management within Industry 4.0 landscape, with the goal to provide future research possibilities. The recent bibliometric analysis carried out by Maganga and Taifa (2023) ranked Quality 4.0 into seven dimensions, beginning with big data management as the top-ranked, followed by application of Industry 4.0 technologies, integration, digitalisation, smart machineries/factory, real-time acts, and concluding with robotics as the final dimension further affirms the ideas of Quality 4.0 as a multi-dimensional concept.

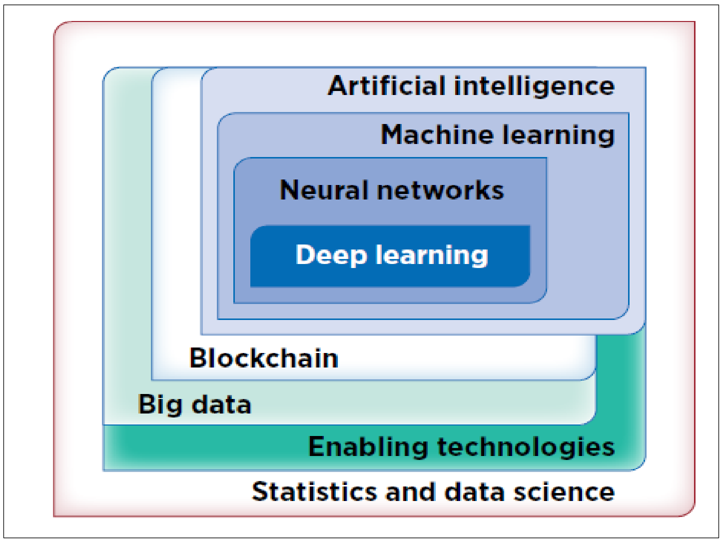
In summary, it seems to be a consensus among the authors that Quality 4.0 is a multi-faceted concept. Its core is built around people, process and technology meta framework, reflecting the pioneering idea from Jacob (2017a). This perspective is further reinforced by various empirical studies and literature reviews that classify Quality 4.0 into multiple dimensions, emphasising its holistic nature. This study adopts and supports the view that Quality 4.0 is best understood as a multi-dimensional framework, as it provides a comprehensive approach to integrating digital transformation with traditional quality management. By structuring Quality 4.0 around people, process, and technology, this framework ensures a balanced perspective, capturing the interplay between human expertise, organisational processes, and technological advancements in driving quality excellence.

2.3.3 Quality 4.0 Tools

In the past decade, the costs of key technologies such as advanced sensors, smart algorithms, and powerful computing have dropped significantly, making it easier for organisations to integrate them into their Quality 4.0 digital strategies. Hence, this era is seen as a pivotal moment in advancing the digital renaissance. Among those Quality 4.0 tools include data science, machine learning, enabling technologies, deep learning, blockchain, big data, and artificial intelligence (Radziwill, 2018).

Although Industry 4.0 has accelerated in the past decade, Quality 4.0 adoption is still at its infancy level (Küpper et al., 2019; Turner & Oakland, 2021) and the concrete connections to companies and jobs seems still appear unclear due to full deployment of Quality 4.0 tools or technologies is either currently underway or still in the future preparation stage. An ecosystem of Quality 4.0 tools has been created to facilitate the digital transformation as depicted in Figure 2-2 (Radziwill, 2018). It is imperative to understand the relationship among these areas and how they complement each other to bring the company towards corporate sustainability goals.

Figure 2-2:
The Ecosystems of Quality 4.0 Tools



Source: Radziwill (2018)

Radziwill (2020) made a substantial effort to dissect Quality 4.0 as a crucial initiative for driving digital transformation. She emphasised how emerging technologies augment connectedness, intelligence, and automation to address practical challenges across various industries. AI spans a wide range of applications, including robotics, language processing, and computer vision, while neural networks and machine learning amplify capabilities in data analysis and decision making. Deep learning further improves image classification and pattern recognition. Blockchain increases transparency and security, whereas big data provides infrastructure for managing large datasets. Enabling technologies include AR, VR, cloud computing, and IoT, with data science facilitating the integration of diverse datasets for advanced analytics.

Maganga and Taifa (2023) carried out an in-depth review of the conceptualisation of Quality 4.0, highlighting technological utilisation in manufacturing industries. Their analysis reinforced Radziwill (2020) perspectives by emphasising advanced digital technologies, further highlighting the diverse technological landscape of Quality 4.0. A detailed understanding and careful selection of the right tools can greatly benefit organisations, and the guideline provided by Radziwill (2020) will serve as valuable resource for organisations to refer to before making investments decisions.

2.4 Quality 4.0 Adoption

Quality 4.0 is a breakthrough in quality management development. However, its diffusion has been slow, particularly in the global manufacturing sector. This is even more evident in developing countries such as Malaysia, where adoption challenges persist. Rogers (2003) described a five-step innovation-decision process that guides individuals from acquiring initial knowledge about an innovation, to creating an attitude, deciding whether to adopt or reject it, implementing the innovation, and ultimately confirming their decision. Although originally designed for individual adoption, this model is equally applicable to organisations. Rogers (2003) defines an organisation as a stable arrangement of individuals who coordinate to pursue common goals within a hierarch and a division of labour.

Early literature on Quality 4.0 predominantly focused on creating awareness by defining its concepts, dimensions, and tools. However, recent studies have expanded to explore factors influencing adoption, including motivation, barriers, readiness factors, and enablers that drive the progression from the knowledge stage to persuasion stage in the innovation-decision process. In organisational setting, especially within business entities, the diffusion of innovations takes considerably longer during the initiation stage due to involvement of multiple stakeholders. Unlike individual adoption, which is often quicker and based on personal decision-making, organisations require a formalised process that include approvals, testing, and budgeting. Consequently, the adoption decision can take months, even years, to materialise.

This section will delve into critical areas influencing the adoption of Quality 4.0, including motivations, barriers, readiness factors, and finally key factors lead to making adoption decision. Understanding these elements is essential in understanding how organisations navigate the complex journey from awareness to adoption. While motivation drives interest and intent, various barriers can impede progress. Readiness factors determine whether a company is preferred to embrace Quality 4.0. Finally, key adoption factors play the final decisive role in pushing organisations toward adoption.

2.4.1 Motivation

Scholars acknowledged that the Quality 4.0 adoption level is still low and higher commitment including resources are needed for the next few years based on inputs from early adopters of Quality 4.0 transformation (Mckendrick, 2020). The adoption of Quality 4.0 in manufacturing sector is driven by various motivations identified in recent studies. Maganga and Taifa (2023) highlighted the important role of big data tools in supporting decision making, fostering continuous improvement, and enhancing customer satisfaction by aligning with Lean and Sig Sigma methodologies. Their study emphasised the importance of data-driven problem solving, remote monitoring, and virtual tracking in improving productivity. Additionally, the incorporation of predictive analytics and artificial intelligence contributed to waste reduction, improved transparency, and enhanced service filed data. Similarly, Swarnakar et al. (2023) discussed how Quality 4.0 facilitates data extraction and analysis, resulting in better customer service, enhanced data security, and a reduction in manual tasks through digitised processes. They highlighted the role of automated quality inspection in ensuring transparency in production, minimising defects, and reducing waste. Furthermore, their research pointed out that the implementation of Quality 4.0 fosters agility, cost savings, and greater involvement of employees in quality management.

Wawak et al. (2023) emphasised the long-term competitive advantages associated with Quality 4.0 adoption, particularly through the interconnection of processes at different management levels. Their findings suggested that organisations benefit from improved performance flexibility, enhanced risk management, and cost optimisation. Additionally, the ability to customise products and involve employees in decision-making fostered a dynamic and adaptive manufacturing environment. Alsadi et al. (2024) further stressed the importance of big data in ensuring reliable and accurate quality management. They highlighted how data-driven approaches optimise decision making, minimise human errors, and boost the overall efficiency of business operations. Their study suggested that Quality 4.0 helps promote sustainability and reduce environmental impact by minimising waste and optimising resource utilisation.

A comparative analysis of these studies revealed several recurring motivations. Among them include improved agility, data-driven decision making, waste reduction, and enhanced transparency in production. The importance of artificial intelligence, predictive analytics, and big data is consistently emphasised as essential in driving efficiency and cost optimisation. Additionally, greater employee involvement and business process streamlining emerge as critical factors contributing to long-term competitiveness. Overall, these findings suggest that the implementation of Quality 4.0 goes beyond technological advancements. It also involves cultivating continuous improvement culture and adaptability across manufacturing organisations.

2.4.2 Barriers

It is crucial to consider not only motivations, but also barriers in gaining a comprehensive understanding of this new concept, as the adoption process is inherently challenging and complex. Antony, Sony, et al. (2023) identified a lack of resources, misalignment between Quality 4.0 and corporate strategy, and unclear benefits as major obstacles. They also highlighted high implementation costs, financial constraints, organisational culture challenges, and the absence of senior management support and training as significant hurdles. Similarly, Swarnakar et al. (2023) emphasised the challenges related to investment in new systems, and the need to convince human resources management about the value of such investments. They highlighted difficulties in using both old and new systems simultaneously, the shortage of skilled personnel, and the complexity of taking corrective actions. Additionally, issues such as data interpretation difficulties, selecting appropriate analytical tools, and fostering a digital mindset within the workforce are identified as key challenges. Aligning existing Quality Management System (QMS) with Quality 4.0 practices, recognising actual organisational needs, and ensuring continuous staff training are also reported as significant barriers.

Wawak et al. (2023) pointed to financial limitations, an absence of long-term quality management strategies, and the necessity for new knowledge and skills as primary obstacles. They also highlighted the passive approach of top management and the difficulties in fostering cooperation between Quality Management (QM) professionals and IT specialists. Alsadi et al. (2024) further reinforced financial investment as a major challenge, along with insufficient knowledge and skills required for implementation. They emphasised the impact of organisational culture and change resistance, driven by a perceived lack of urgency. Additionally, inadequate management support and low organisational readiness contributed to implementation difficulties.

Virmani et al. (2024) focused on the change resistance challenges and insufficient understanding of Quality 4.0 concepts. Limited access to resources, data, technology, and automation further hindered adoption. Fadilasari et al. (2024) expanded on these barriers by highlighting issues related to lack of leadership, poor management support, weak organisational learning, and insufficient collaboration between stakeholders. They also emphasised concerns related to financial issues, cybersecurity, and data management as critical barriers.

By comparing these studies, it was found that the most frequently mentioned barriers to Quality 4.0 adoption include financial constraints, insufficient management support, change resistance, skill gaps, and challenges related to organisational culture. High initial investment costs and the absence of clear strategic alignment often leads to reluctance from top management. Moreover, insufficient training and expertise hinders workforce readiness of Quality 4.0 implementation. Change resistance, fuelled by a sense of complacency and a limited understanding of how Quality 4.0 can benefit the organisations, worsens these challenges. Additionally, inadequate collaboration between quality management and IT functions creates difficulties in aligning traditional systems with digital transformation initiatives. These findings highlight the need for structured change management strategies, investment in skills development, and stronger leadership commitment to facilitate effective adoption. Senior quality practitioners and decision-makers should carefully consider these barriers before embarking on the transformation journey within their organisations.

2.4.3 Readiness

In terms of readiness factors, comprehensive literature review was conducted by researchers, and eight key readiness factors are empirically studied (Sony et al., 2021). The literature review by Sony et al. (2020) also summarised key technological aspects of Quality 4.0. Similarly, Thekkoote (2022) conducted a comprehensive review and pinpointed ten essential factors that lead to effective Quality 4.0 implementation. He highlighted the pivotal importance of connectivity, data analytics, and applications development in preparing organisations for Quality 4.0 adoption. The study also emphasised scalability, data management, and organisational culture as foundational elements, suggesting that robust technological infrastructure and a culture receptive to innovation are essential for integrating Quality 4.0 practices effectively.

Expanding on this, Maganga and Taifa (2023) performed a bibliometric analysis of journal articles from leading databases and highlighted crucial enablers that can facilitate Quality 4.0 adoption. These include big data capabilities, collaboration, leadership support, trained and competent personnel, and enabling technologies. Their analysis suggested that Quality 4.0 readiness extends beyond technological capabilities to encompass organisational, human, and strategic dimensions, ensuring a cohesive transition to advanced quality management systems. Zulfiqar et al. (2023) performed a Quality 4.0 assessment readiness in packaging companies and concluded five readiness factors that can empirically supported Quality 4.0 adoption. Their work highlighted the need for strong leadership commitment and a culture of continual improvement, aligned with international quality standards to support Quality 4.0 adoption. This perspective reinforces the importance of aligning internal processes and leadership strategies with technological advancements to achieve quality excellence. An exploration study carried out by Antony, Sony, et al. (2023) among services and manufacturing companies in Europe, America, and Asia also provided an insight into the factors that determine readiness for adopting Quality 4.0. Their studies underscore the interconnections of stakeholders (internal and external), emphasising the need for a customer focused, and strategically aligned method to ensure long-term success in Quality 4.0 adoption.

A comparison of these studies identified several recurring readiness elements that are critical to Quality 4.0 adoption. Among them include top management support, leadership, organisational culture, and training. These findings emphasise the critical role of leadership, cultural readiness, skilled workforce, and technological infrastructure in Quality 4.0 adoption. These readiness elements form the foundation for exploring key factors driving the Quality 4.0 adoption process in this study.

2.4.4 Adoption Factors

Corporate sustainability performance is a crucial strategic priority that must be aligned before adopting Quality 4.0. In today's complex and highly competitive global landscape, corporate sustainability is not an option, but a critical factor for business survival and long-term success. Hence, by synthesising the information gathered from knowledge and persuasion stages of innovation decision making process, seven key adoption factors as independent variables influencing the diffusion of Quality 4.0 have been identified, which cover relative advantage, AI compatibility, top management support, transformation leadership, organisational culture, external support, and market pressure. By understanding these factors, manufacturing companies can develop more effective strategies to accelerate the diffusion of Quality 4.0, ensuring a smoother transition from awareness to adoption while enhancing corporate sustainability and competitive advantage.

2.4.4.1 Relative Advantage

Relative advantage is viewed as the perceived improvement of an innovation over existing practice. A higher perceived relative advantage leads to faster adoption (Rogers, 2003). This is one of the key innovation characteristics to encourage innovation diffusion and empirical evidence have proven it to be a consistent predictor of adoption towards new innovations (Aligarh et al., 2023; Badghish & Soomro, 2024; Choudhury & Karahanna, 2008; Hmoud et al., 2023; Lian et al., 2014; Mohammed et al., 2024; Premkumar & Roberts, 1999; Shahzad et al., 2023; Tiwari et al., 2023; Tornatzky & Klein, 1982). While other innovative characteristics such as complexity, observability, and trialability also influence innovation adoption, relative advantage often serves as the primary motivator. Without a clear perception of the benefits an innovation offers over current practices, companies may be reluctant to invest the necessary resources for implementation. Therefore, emphasising the relative advantage of Quality 4.0 can significantly enhance its adoption within companies.

In the context of Quality 4.0, relative advantage extends beyond immediate operational gains to include broader strategic and quality outcomes related to corporate sustainability performance. As Quality 4.0 adoption involves the integration of advanced digital technologies into established quality management systems, manufacturing companies must clearly perceive how these new initiatives enhance quality performance, enable data driven decision making, and strengthen competitive positioning. The perceived ability to improve process control, support proactive quality management, and align quality practices with business strategy reinforces its relative advantage over traditional quality management approaches (Sony et al., 2020, 2021). Furthermore, aligning quality management with Industry 4.0 technologies has been shown to enhance strategic decision making and corporate competitiveness, thereby increasing the perceived benefits of Quality 4.0 adoption (Liu et al., 2023). As a result, relative advantage plays a critical role in justifying technology investment decisions and sustaining corporate commitment to Quality 4.0 adoption.

2.4.4.2 AI Compatibility

Rogers (2003) defines compatibility as the alignment of an innovation with adopters' values, experiences and needs. The more compatible the innovation is with these factors, the quicker it will be adopted. This characteristic significantly influences the diffusion process, with research consistently highlighting compatibility is positively related to the adoption of new technologies such as AI integration into existing systems (Badghish & Soomro, 2024; Rogers, 2003; Russo, 2024; Teo et al., 1997; Teo & Pian, 2003).

Although Rogers' original conceptualisation emphasis values, experiences, and needs, it has been widely adopted and extended in technology adoption research to capture the degree to which new technologies align with existing technological infrastructures, operational processes, and system architectures (Awa et al., 2017; Chittipaka et al., 2023; Prakash, 2025). In line with this stream of research, this research builds on Rogers' compatibility construct as a theoretical foundation and adapts it to the Quality 4.0 context, defining AI compatibility as the degree to which AI enabled Quality 4.0 solutions align with an organisation's existing technology structure, infrastructure and procedures, values and norms, experiences, and the information sharing needs (Awa et al., 2017; Prakash, 2025; Teo & Pian, 2003).

Artificial Intelligence (AI) enables machines to demonstrate intelligent behaviour, adapt to changing conditions, and enhance human creativity and cognitive abilities by leveraging collective intelligence to solve a variety of problems (MOSTI, 2021). In Malaysia, the AI market holds substantial promise, with projections indicating a stable growth path. It is anticipated to grow at a yearly rate of 27.63% between 2025 and 2030, ultimately reaching a value of US$3.59 billion by year 2030 (Statista, 2024). In addition, the Malaysian government is actively promoting its integration across various sectors as what has been emphasised by Prime Minister Anwar Ibrahim to speed up AI adoption to drive the nation's digital economy forward (Sipalan, 2024). Given these recent developments, prioritising AI compatibility within Quality 4.0 adoption is not only timely, but also essential for manufacturing companies aiming to remain competitive in Malaysia's evolving industrial landscape.

2.4.4.3 Top Management Support

Top management support refers to leaders recognising, promoting, and enabling innovation with the organisation. Research across various types of technology adoption, including cloud computing, mobile marketing and others has consistently demonstrated top management support is positively correlated to new technologies adoption and implementation. These findings endorsed top management plays a critical role in driving innovation within organisations (Antony, Sony, et al., 2023; Borgman et al., 2013; Hmoud et al., 2023; Lian et al., 2014; Maduku et al., 2016; Mohammed et al., 2024; Premkumar & Roberts, 1999; Shahzad et al., 2023).

Shahzad et al. (2023) recently explored the vital role of top management support in Industrial 4.0 adoption among Malaysian SMEs. Their involvement significantly influences the process by advocating its use, initiating supportive initiatives, prioritizing it strategically, and actively engaging with related developments. In the similar manner, Mohammed et al. (2024) also emphasised that top management support is a pivotal organisational factor positively influencing Business Intelligence and Analysis (BIA) adoption. Their support facilitates resource allocation, overcome adoption barriers, and shapes an environment conducive to effective BIA utilisation.

The adoption of Quality 4.0 places extensive demands on leadership, making top management support a decisive factor in guiding digital quality transformation in manufacturing companies. Quality 4.0 adoption typically involves significant changes to organisational structures, work practices, and decision-making process. It requires visible commitment from senior leaders. When top management clearly articulates a Quality 4.0 vision, aligns digital quality transformation initiatives with business strategy, and allocates adequate resources, it creates an environment that legitimises change and reduces resistance within the organisation (Sony et al., 2020, 2021). In addition, top management plays a critical role in fostering a culture that values data driven decision making and continuous improvement, both of which are central to Quality 4.0 adoption (Antony, Sony, et al., 2023). Through strategic guidance, resource commitment, and cultural leadership, top management support becomes a key mechanism enabling the successful adoption and integration of Quality 4.0.

To sum up, top management support is indeed a crucial driver of innovation adoption, as evidenced by various studies across different innovation advancements.

Furthermore, existing literature also acknowledges it as both a significant barrier and a critical readiness factor for innovation adoption including Quality 4.0, reinforcing its role as an essential determinant in the successful adoption and integration of innovation.

2.4.4.4 Transformational Leadership

Burn first introduced transformational leadership concept in 1978 and later refined by Bass in 1985 (Bass & Riggio, 2006). This leadership style is characterised by four key components, namely idealised influence, inspirational motivation, intellectual stimulation, and individualised consideration (Bass & Riggio, 2006). Research by Laohavichien et al. (2009) found that transformational leadership has a significant positive effect on both infrastructure development and core quality management practices. In addition, studies by Nasir et al. (2022) and Usman (2020) have highlighted the effectiveness of transformation leadership in fostering successful organisational change. Likewise, another research by Virmani et al. (2024) acknowledged the influence of transformational leadership, leveraging its principles to overcome barriers in adopting Quality 4.0.

Recent study by Jun and Lee (2023) reported that transformational leadership foster innovation adoption by enhancing followers' commitment to change. This effect is amplified in environments that support creativity. The study highlighted that leadership alone is not sufficient. It must be complemented with a supportive organisational context to maximise innovative outcomes. In complex and resource-intensive initiatives such as Quality 4.0 adoption, formal governance structure, budgetary control, and cross-functional coordination may play a more immediate role in shaping adoption decisions than leadership alone. This dual approach provides a deeper understanding into how transformational leaders can facilitate innovation in dynamic, change-oriented setting.

Aligning with this observation, Nguyen et al. (2023) demonstrated that transformational leadership primarily influences organisational outcomes through its impact on organisational culture, indicating that leadership effects are mediated rather than direct. Similarly, Juliasa et al. (2025) found that organisational learning mediates the relationship between transformational leadership and innovation, further suggesting that leadership contributes to innovation adoption by strengthening organisational capabilities rather than acting as a standalone driver. As such, transformational leadership may function as an enabling or complementary factor that supports other organistional drivers of adoption.

In conclusion, the contribution of transformation leadership is significant in supporting innovation, quality management, and organisational change. Its foundational components enable leaders to inspire commitment and adaptability among followers and subsequently enhance organisation's capacity for innovation and successfully navigate the evolving landscape of modern industry.

2.4.4.5 Organisational Culture

Organisational culture refers to shared beliefs, norms, and values that define an organisation's identity (Gimenez-Espin et al., 2013). This culture profoundly influences its members, affecting not only their behaviours and performance outcomes, but also how the organisation interacts with its external environment. The organisation fosters a sense of family, encouraging teamwork, dedication, and participation (Sony et al., 2020).

Recent findings by Zhang et al. (2023) highlighted that organisational culture significantly shapes innovation adoption, but its impact is channelled through the social context and performance management context rather than directly affecting innovation performance. They concluded that for effective innovation adoption, organisations must strategically develop management contexts that amplify positive cultural traits and mitigate negative ones, ensuring a culture conducive to sustainable innovation performance. Similarly to that, Virmani et al. (2024) emphasised the critical role organisational culture plays in Quality 4.0 adoption and addressing solutions to tackling related barriers.

An organisational culture that supports Quality 4.0 adoption is characterised by openness to changes, continuous learning, and collaboration across functional boundaries. As Quality 4.0 adoption relies heavily on data integration, digital connectivity, and cross functional decision making, cultures that promote transparency, trust, and knowledge sharing are more conducive to successful adoption (Sony et al., 2021). Such cultures encourage employees to engage with digital quality tools, experiment with new practices, and use data driven insights to improve quality outcomes. In contrast, rigid or siloed cultures may limit information flow and inhibit the effective use of Quality 4.0 technologies. Therefore, an organisational culture that values innovation, employee involvement, and proactive change management plays a critical role in enabling Malaysian manufacturing companies to translate Quality 4.0 adoption into improved corporate sustainability performance (Antony, Sony, et al., 2023; Sony et al., 2021).

In essence, organisational culture significantly shapes behaviours, performance and innovation adoption within a company. To drive effective innovation and Quality 4.0 adoption, organisations need to deliberately cultivate a supportive culture that enhances beneficial characteristics and addresses contextual barriers, ensuring long-term corporate sustainability and success.

2.4.4.6 External Support

External support includes the readiness, resources, and assistance needed for effective technology adoption (Mohammed et al., 2024; Premkumar & Roberts, 1999). Adoption of innovations is complex and normally comes with complex and multifaceted concepts especially involving industrial revolution 4.0 and its associated innovations such as Quality 4.0 especially during the initial stages of adoption. Hence, external support from various parties such as vendors, industry associations, companies within the same or different sectors, and standardisation organisations can be crucial success factors for implementing innovations (Jayashree et al., 2022; Masood & Egger, 2019; Mohammed et al., 2024).

Recent research by Aldridge et al. (2023) highlighted how external support, through structured and dynamic interventions, plays a multifaceted role in driving innovation adoption by enhance capacity, fostering collaboration, and ensuring sustainable adoption and implementation. The study provided a detailed theory of change for External Implementation Support (EIS), emphasising its mechanisms, and practical applications in fostering innovation adoption.

However, existing literature also suggests that the influence of external support may be contingent on internal organisational conditions in innovation adoption (Bernal-Torres et al., 2025; Zhou et al., 2024). In resource intensive and strategically complex initiatives such as Quality 4.0 adoption, internal factors including top management support, organisational culture, and governance structures may play a more immediate role in shaping adoption decisions. Under such conditions, external support may function more as an enabling or complementary mechanism that reduces uncertainty, transfers knowledge, or accelerates implementation once internal readiness has been established, rather than acting as a decisive driver of adoption on its own (Aldridge et al., 2023; Zhou et al., 2024). Furthermore, the effectiveness of external support may vary depending on firm size, resource availability, and the maturity of applicable industry standards, indicating potential boundary conditions in its direct influence on Quality 4.0 adoption (Bernal-Torres et al., 2025; Senna et al., 2022).

In summary, external support remains an important component in technology-based innovation adoptions. It contributes by helping organisations build resilience, leverage external expertise, and participate in collaborative ecosystems that support long term corporate sustainability. In the context of dynamic Quality 4.0 adoption landscape, external support may operate in conjunction with internal organisational drivers, contributing to adoption outcomes within a broader organizational and environmental context.

2.4.4.7 Market Pressure

Market pressure represents the influence exerted on organisations by competitors, customers, or suppliers, urging them to embrace new innovations. As this pressure intensifies, organisations are more likely to adopt innovative solutions to strengthen their competitive edge (Jayashree et al., 2022; Su et al., 2023). Researchers suggested that such market pressure drives innovation or technologies adoption and positively correlates external competitive forces to a greater willingness to innovate (Jayashree et al., 2022; Maduku et al., 2016; Su et al., 2023).

Latest research by Su et al. (2023) revealed that market pressure is a booster, setting the adoption target, while interacting with organisational readiness (psychological, technical, cognitive) as an enabler. Adoption strategies evolve only when readiness aligns with the intensity of market pressure. The study highlighted that market pressure triggers and shapes the evolution of strategies along the validation, cloning and foresight path. It dictates the urgency, scope, and complexity of adoption pushing organisations to adapt to competitive landscape.

In the context of manufacturing companies operating in export-oriented environments such as Malaysia, increasing requirements related to product traceability, sustainability reporting, and compliance with international standards create strong incentives to adopt advanced digital quality solutions. For example, increased scrutiny on carbon emissions (European Commission, 2025), supply chain transparency, and quality assurance across international markets (CBP, 2025) has intensified expectations for data accuracy, real time monitoring, and documentation capabilities. Such pressures encourage manufacturing companies to adopt Quality 4.0, including digital traceability systems and data-driven quality management systems to meet external stakeholder requirements and remain competitive in global value chains. As such, market pressure functions not only as a trigger for adoption, but also as a catalyst shaping the scope and urgency of Quality 4.0 implementation.

In short, market pressure is a powerful force driving organisations to adopt innovations, as it originates from external forces, such as rivals, customers, or suppliers. The alignment of organisational readiness with market forces is key to ensuring that innovation adoption is not only timely, but also strategically sound, enabling companies to preserve their competitive advantage in an ever-evolving marketplace.

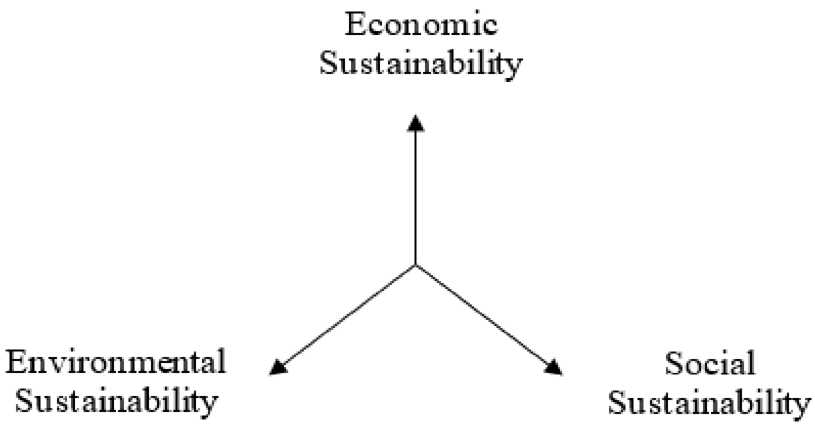
2.5 Corporate Sustainability Performance

Corporate sustainability has evolved over time, but its core principle remains consistent, which is to balance present and future needs of stakeholders at business level. In recent studies, corporate sustainability was described as corporate policies and investment strategies designed to address the information needs of both current and future stakeholders (Özkan & Ağ, 2021) . Similarly, Rasche et al. (2023) emphasised the criticality of corporate sustainability in managing the interconnected ecological, social, and economic systems in which a business operates. By adopting this holistic approach, companies can achieve a positive, long-term impact, balancing environmental health, societal well-being, and stakeholder value. To effectively measure corporate sustainability performance, it is essential to concurrently consider and integrate three pillars of corporate sustainability as illustrated in Figure 2-3.

According to Özkan and Ağ (2021), corporate sustainability performance refers to the extent to which organisations consider economic, social, and environmental dimensions in their business activities and their consequences for both society and the business. These definitions are aligned with the triple bottom-line (TBL) approach

(Dyllick & Hockerts, 2002; Elkington, 1997; Nogueira et al., 2025), which is one of the widely accepted approaches to measure corporate sustainability performance because it supports all aspects of sustainability covering people (social aspect), planet (environmental impact), and profit (economic impact). It is also recognised as a business strategy that influences a company's economic, environmental, and social impacts, ultimately promoting sustainable development (Nogueira et al., 2025; Schaltegger et al., 2003).

Figure 2-3:
Three Pillars of Corporate Sustainability Performance



2.5.1 Economic Sustainability

Dyllick and Hockerts (2002) argued that companies with economic sustainability not only maintain steady cash flow to ensure liquidity, but also consistently provide superior returns to their shareholders. It involves sustaining economic capital, which covers financial capital, tangible capital and intangible capital. Similarly, Alsayegh et al. (2020) highlighted that economic sustainability performance includes both financial costs and benefits, representing a company's long-term profitability and financial stability. It can be assessed through factors such as operational effectiveness, efficiency, and productivity over time. Typically, this performance is reflected in financial statements using key financial indicators, such as economic value added (EVA), return on assets (ROA), and return on equity (ROE).

Mal et al. (2023) further reinforced the importance of economic sustainability performance such as profitability and growth because a company's financial success and long-term viability depend on its capacity to generate revenue, reinvest in sustainable initiatives, and withstand economic shocks. In summary, economic sustainability serves as the foundation for corporate sustainability, ensuring that businesses can support environmental and social responsibilities while maintaining financial resilience.

2.5.2 Environmental Sustainability

At the business level, environmental sustainability requires companies managing natural resources responsibly so that they do not deplete them faster than they can regenerate or by developing alternatives. These companies are committed to ensuring their emissions remain within the environment's capacity for absorption and minimising activities that harm ecosystem services. They prioritise practices that support long term environmental health while reducing their ecological footprint (Dyllick & Hockerts, 2002). Environmental sustainability performance is usually managed through an environmental management framework, which helps minimise and control environmental impacts through the supply chain. This involves assessing key input factors like materials, energy, and water consumption, as well as output indicators such as emissions, waste, and effluents to ensure more sustainable operations (Alsayegh et al., 2020).

In the same manner, Mal et al. (2023) acknowledged environmental sustainability as minimising the ecological footprint of business activities through responsible resource management and pollution control. Their study highlighted performance monitoring in the dimensions of environmental management policies, waste management, and sustainable products. In short, environmental sustainability is essential for reducing the negative impact of business operations on ecosystems, ensuring long-term ecological balance, regulatory adherence and achieving corporate sustainability.

2.5.3 Social Sustainability

Companies prioritising social sustainability enhance community well-being by investing in human capital and strengthening social ties. They manage social capital effectively, aligning stakeholders with their values and fostering support (Dyllick &

Hockerts, 2002). Alsayegh et al. (2020) explained that social sustainability performance reflects how well a company put its social goals into action. This includes key aspects such as fair working conditions, employee health and safety, working relationships, well-being, diversity, human rights, far labour practices, community engagement, and philanthropic efforts.

Likewise, Mal et al. (2023) emphasised that social sustainability requires company's commitment to ethical labour practices, stakeholder engagement, and community development. The study identified three social sustainability performance dimensions, covering responsibilities toward shareholders, community, and employees. To conclude, social sustainability ensures that businesses contribute positively to society by fostering ethical corporate behaviour, supporting employees, and engaging with communities.

2.5.4 Quality 4.0 Adoption and Corporate Sustainability Performance

A wide range of studies have indicated a positive relationship between the adoption of Quality 4.0 and improved corporate sustainability performance across all three key dimensions: economic, environmental, and social (Antony, Sony, et al., 2022; Bag et al., 2021; Bogoviz et al., 2023; Kirchherr et al., 2017; Küpper et al., 2019; Nenadál et al., 2022; Oláh et al., 2020; Sony et al., 2021). Antony, Sony, et al. (2022) has recently carried out an integrative literature review provided valuable insights into how Quality 4.0 can influence the three core dimensions of corporate sustainability. An exploratory qualitative study conducted by Antony, Swarnakar, et al. (2023) highlighted early adopters of Quality 4.0 gained a competitive advantage over late adopters, emphasising the positive impact on corporate sustainability. Integrating corporate sustainability with Quality 4.0 ensures that companies can drive innovation, enhance efficiency, and remain resilient in an ever-evolving market.

2.6 Underpinning Theories

Quality 4.0 is closely linked to Industry 4.0 and emphasizes the prominent role of technology together with existing quality management practices in transforming the quality landscape. As such, the adoption of Quality 4.0 practices is seen as a form of innovation diffusion and execution within the quality management field.

When studying innovation or technology diffusion and adoption within organisations, two prominent theories are often utilized: the Diffusion of Innovation (DOI) theory (Rogers, 2003) and the Technology-Organisation-Environment (TOE) framework (Tornatzky et al., 1990). Both theoretical groundworks provide valuable frameworks for understanding how innovations or technology are adopted and diffused within organisational contexts (Oliveira et al., 2014). However, TOE framework is chosen as the host theory for Quality 4.0 adoption in this research due to its adaptability, allowing researchers to modify factors based on specific research contexts.

On the other hand, Resource-Based View (RBV) theory originated by Barney (1991) and further expanded in 1995 provides a foundational lens to explain how manufacturing companies can leverage their internal resources and capabilities to achieve competitive advantage using the VRIO framework (Barney, 1995). In this study, Quality 4.0 adoption is viewed as a strategic capability that can be considered valuable, rare, inimitable, and organised, enabling manufacturing companies to augment their corporate sustainability performance across economic, environmental, and social dimensions.

In summary, TOE framework helps to facilitate the understanding of Quality 4.0 adoption determinants as an innovation in quality management while RBV theory lays a foundation for comprehending Quality 4.0 adoption as strategy capability for manufacturing companies to achieve improved corporate sustainability performance. Table 2-2 illustrates a summary of the constructs and their underlaying theories supporting the research in this study.

Table 2-2:
Constructs and the Governing Theories

Constructs		**Theories**	
		Technology-Organisation-Environment (TOE)	Resource-Based View (RBV)
Technological Context	Relative Advantage	√	
	AI Compatibility	√	
Organisational Context	Top Management Support	√	
	Transformational Leadership	√	
	Organisational Culture	√	
Environmental Context	External Support	√	
	Market Pressure	√	
Quality 4.0 Adoption		√	
Corporate Sustainability Performance	Economic Sustainability		√
	Environmental Sustainability		√
	Social Sustainability		√

2.6.1 Technology-Organisation-Environment (TOE) Framework

In 1990, Tornatzky and his colleagues introduced the TOE framework, which explains how innovation takes place in an organisational setting. The framework consists of three essential components that affect the adoption of innovation, namely technology, organisation, and environment.

Technology context encompasses both internal and external technologies that an organisation can leverage for adoption. Meanwhile, the organisational context captures key attributes such as structure, size, management approach, level of centralisation, and resource availability, including human capital and operational slack. Additionally, both formal and informal communication play a crucial role in shaping the internal dynamics of an organisation. One the other hand, the environmental context comprises of external influences such as market dynamics, competitive pressures, and regulatory frameworks, all of which can significantly impact the adoption of innovations (Oliveira et al., 2014; Tornatzky et al., 1990).

TOE's technology context closely mirrors Roger's conceptualisation in Diffusion of Innovations (DOI) theory, while the internal and external organisational factors in DOI align with the organisational context in TOE. Despite these similarities, key distinctions exist between the two. The TOE framework does not explicitly emphasise the role of individual factors, such as top management support, which DOI considers crucial in the organisational context. Conversely, DOI does not consider the impact of the environmental influences, which form a core component of TOE. Integrating DOE within the TOE framework gives a more holistic approach to comprehending innovation by encompassing technological, organisational, and environmental dimensions. They complement each other, making their combined application a widely adopted approach in research on innovation diffusion (Jayashree et al., 2022; Oliveira & Martins, 2011).

The TOE framework is selected as the primary theorical lens for examining Quality 4.0 adoption in this research due to its flexibility, which allows researchers to tailored contextual dimensions according to the specific needs and setting of the research. In addition, the combination of DOI within TOE provides a holistic lens for understanding Quality 4.0 adoption in organisations setting such as manufacturing companies in Malaysia. In the technological context, DOI's concept of relative advantage aligns with the AI compatibility in Quality 4.0 adoption as companies are more likely to embrace innovation such as Quality 4.0 technologies that enhance efficiency and performance. The organisational context in TOE comprises of internal factors such as top management support, transformational leadership, and organisational culture, in which DOI addresses them through its focus on opinion leaders, change agents, and the broader social system. Top management support and transformational leadership serve as internal change agents, shaping employees' perceptions of Quality 4.0's benefits during DOI's persuasion and decision stages, while organisational culture influences the compatibility of Quality 4.0 adoption with existing norms, a critical DOI factor for adoption. In terms of environmental perspective, TOE highlights external support and market pressure as key adoption drivers, complementing DOI's emphasis on the role of social system and external influence in innovation diffusion.

By integrating DOI theory within the TOE framework, this research will capture both individual and organisational decision-making processes while accounting for the technological, organisational, and environmental factors that shape Quality 4.0 adoption.

This synergistic approach provides a comprehensive perspective, ensuring that innovation characteristics, internal organisational dynamics and external market forces are holistically considered in understanding how Malaysian manufacturing companies navigate the Quality 4.0 adoption process.

2.6.2 Resource-Based View (RBV) Theory

Resource-Based View (RBV) theory was introduced by Barney (1991) and remains as a highly influential theory in strategic management and related field for over three decades (Helfat et al., 2023). Barney (1991) originally posited that sustainable competitive advantage arises from the possession and strategic utilisation of firm-specific resources that are valuable, rare, inimitable, and non-substitutable, forming the VRIN framework. As outlined by Barney and Hesterly (2010), a firm's resources and capabilities can be broadly classified into four types, namely financial, physical, human (individual) and organisational resources.

Four years after introducing the RBV theory, Barney (1995) expanded the theory by stressing the significance of developing sustained competitive advantage through unique resources and capabilities that a firm possesses-an approach referred to as the "looking inside" perspective. In this extension, he refined the original VRIN framework to VRIO framework by bringing the element of organisation, highlighting that firms must be organised to fully exploit their strategic resources and capabilities. This inward-looking perspective represented a shift from the traditionally external, industry-focused views of competitive strategy.

By 2001, the RBV had evolved into a more mature and widely accepted framework. Barney et al. (2001) reaffirmed its relevance in strategic management research, while also recognising the need for integration with complementary perspectives such as dynamic capabilities, which offer deeper insights into how resources evolve and adapt in rapidly changing business environments. This perspective also laid the groundwork for linking RBV to emerging areas such as the innovation and technology adoption.

In more recent developments, Helfat et al. (2023) highlighted that the RBV theory must be renewed to remain relevant, especially in new contexts such as digitalisation, artificial intelligence (AI), stakeholders and sustainability. Their work introduced extended concepts such as resource redeployment and market shaping through resources and capabilities to better reflect contemporary strategic landscapes. Importantly, they emphasised that RBV's core principles can be adapted to account for value creation not just for shareholders, but also for broader stakeholder groups, aligning well with the triple bottom line (TBL) approach of addressing corporate sustainability performance.

In this study, RBV theory can be applied to elucidate how Quality 4.0 adoption influences corporate sustainability performance because it provides a strong foundation for viewing Quality 4.0 adoption as a strategic capability. Besides, this capability embedded with Quality 4.0 technologies such as AI, big data analytics, and IoT are not just tools, but can be regarded as valuable, rare, inimitable, and well-organised resources, aligning with the VRIO framework for sustained competitive advantage. In addition, these resources and capabilities support improved corporate sustainability performance, by driving economic gains, reducing negative environmental impact, and advancing corporate social responsibility. The renewed RBV perspective by Helfat et al. (2023) also highlights the relevance of sustainability and stakeholder engagement, reemphasising its applicability in evaluating corporate sustainability performance through the Triple Bottom Line (TBL) dimensions. This further strengthens the theoretical application of RBV theory in this research.

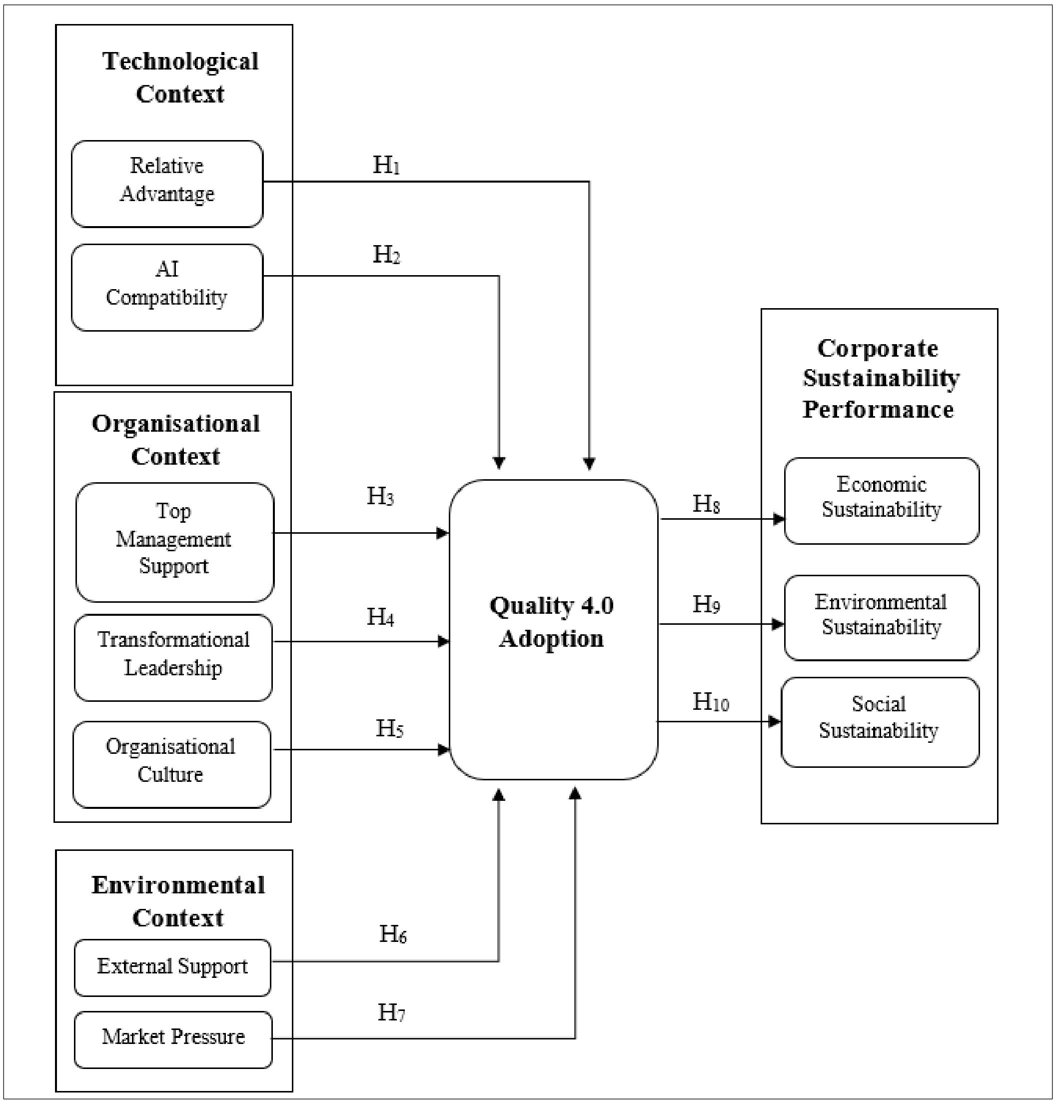
2.7 Conceptual Framework

Figure 2-4 exhibits a conceptual framework which has been proposed and adapted based on the integrated TOE framework from previous research studies as the foundation to suit our research scope in this study (Antony, Sony, et al., 2022; Dias et al., 2022; Ghatak & Garza-Reyes, 2024; Jayashree et al., 2022; Saha et al., 2022; Sony et al., 2020, 2021).

The model is a stepwise analysis which covers factors affecting Quality 4.0 adoption and the impact of Quality 4.0 adoption on corporate sustainability performance among manufacturing sector in Malaysia. Seven independent variables known as relative advantage, AI compatibility, top management support, transformational leadership, organisational culture, external support and market pressure have been chosen towards Quality 4.0 adoption. The impact of Quality 4.0 adoption in helping companies within the context of manufacturing sector in Malaysia to improve corporate sustainability performance (economic, environmental, and social dimension) which is also known as our dependent variable in this study will be studied as well.

The relative advantage of Quality 4.0 technologies and AI compatibility have been chosen as the technological factors in the integrated TOE framework to assess its impact on Quality 4.0 adoption. These factors will help determine whether perceived relative advantage and AI technology compatibility will encourage the adoption of Quality 4.0. Within the organisational dimension, factors that are crucial include top management support, transformational leadership and organisational culture. Lastly, external support and market pressure have been selected to explain how environmental dimension can influence Quality 4.0 adoption and its impact on corporate sustainability.

Figure 2-4:
Conceptual Framework



2.7.1 Gaps in Literature

In 2017, LNS research first coined the concept of Quality 4.0 from an industrial perspective. Since then, there is a gradual interest pouring from the scientific community in understanding Quality 4.0 from different aspects, including its definition, theoretical foundations, model constructs, empirical application, industrial adoption levels, and its impact towards organisational performance. However, despite these advancements, the overall development remains in its nascent stage.

While past research has contributed significantly to conceptualising Quality 4.0 and established its fundamentals, a universally accepted adoption and implementation framework is yet to be established (Sony et al., 2021). In addition, a disconnect persists between theoretical discussions and the practical application of Quality 4.0, particularly within the broader context of Industry 4.0 (Oliveira et al., 2025). Methodologically, much of the existing Quality 4.0 literature remain conceptual or exploratory in nature, with relatively limited large scale empirical studies that systematically examine adoption determinants and corporate sustainability performance within a single unified framework. Existing studies have yet to comprehensively examine the impact of Quality 4.0 adoption on corporate sustainability performance. From a population gap perspective, prior empirical research has predominantly focused on organisations in developed economies or specific industrial settings, resulting in limited evidence from developing countries. Research focusing on Malaysian manufacturing companies remains scarce, particularly in identifying key factors of Quality 4.0 adoption and its subsequent impact on corporate sustainability in a single framework, creating a clear research gap in the literature.

Building on the identified research gaps, this study aims to address them in several approaches. Firstly, it will provide empirical evidence on the key factors of Quality 4.0 adoption among manufacturing companies in Malaysia and assess its impacts on corporate sustainability performance. Secondly, it offers a detailed analysis of how specific dimensions within of technology, organisation and environment (TOE) framework influences Quality 4.0 adoption, and how this adoption affects corporate sustainability performance across economic, environmental and social dimensions. To the best of the researcher's knowledge, this research is among the first to empirically examine the relationship between TOE dimensions, Quality 4.0 adoption, and corporate sustainability performance in a unified framework, particularly within the Malaysian manufacturing context. By integrating theoretical insights with real-world implications, this research aims to make valuable contributions to both academic literature and industry practices. It offers a comprehensive understanding of how Quality 4.0 adoption can drive improvements in corporate sustainability, thus bridging the gap between theory and practice.

2.7.2 Justification of the Conceptual Framework

The Technology-Organisation-Environment (TOE) framework has long been recognised as a robust theoretical model for studying the adoption of emerging technologies, making it an idea lens through which to examine the uptake of Quality 4.0 in Malaysian manufacturing companies. Building on recent research by Ghatak and Garza-Reyes (2024), which applied the TOE framework to explore barriers to Quality 4.0 adoption, this study leverages the framework's comprehensive capacity to capture the complex interactions between technological, organisational, and environmental factors. By grounding the study in the TOE framework, it offers a holistic approach to understanding the multifaceted influences on Quality 4.0 adoption, in line with established research.

One notable contribution in this study is the inclusion of the compatibility of artificial intelligence (AI) as a technological factor driving Quality 4.0 adoption. While previous studies have predominantly emphasised organisational factors, limited empirical attention has been given to how emerging technologies such as AI align with existing quality management systems and technology infrastructure. Given AI's growing role in shaping the future of Quality 4.0, this study examines AI compatibility as a theoretically relevant technological factor that warrants empirical investigation. By empirically testing this relationship, the study contributes to clarifying the role of AI integration within the Quality 4.0 adoption context, consistent with the evolving technological landscape highlighted by Min and Kim (2024).

Additionally, while leadership has been acknowledged as an important factor in innovation adoption, the research takes a more focused approach by investigating transformational leadership as an organisational factor associated with Quality 4.0 adoption. Transformational leadership is theoretically aligned with the demands of Quality 4.0, as it supports innovations, articulates a shared vision, and facilitates the cultural change (Sony et al., 2021). By investigating transformational leadership as a specific organisational dimension, this study contributes to a more nuanced understanding of leadership style influence in Quality 4.0 adoption.

Finally, this study employs the Triple Bottom Line (TBL) framework to conceptualise corporate sustainability performance, incorporating economic, environmental, and social dimensions (Elkington, 1997). This holistic approach is especially pertinent in the manufacturing sector, where companies must simultaneously navigate the challenges of maintaining profitability, ensuring environmental stewardship, and meeting social responsibility goals. With growing pressures for sustainable practices in manufacturing, this study contributes to the literature by offering an integrated assessment of corporate sustainability in the context of Quality 4.0 adoption, bridging the gap between quality management practices and sustainable performance outcomes.

To sum up, by integrating the TOE framework, refining technological and leadership dimensions, and applying the TBL approach to corporate sustainability performance, this study contributes to the body of knowledge on Quality 4.0 adoption in manufacturing sector. It will not only deepen theoretical understanding but also offer practical insights that can guide organisations in their adoption of Quality 4.0 and drive long-term, sustainable success.

2.8 Hypotheses Development

2.8.1 Relative Advantage and Quality 4.0 Adoption

Quality 4.0 is a constantly evolving field and requires adequate technology readiness to support the adoption. While Quality 4.0 adoption utilises Industry 4.0 technologies, a study carried out by Shahzad et al. (2023) found a positive and significant relationship between relative advantage of these technologies and their adoption among Malaysian small and medium-sized enterprises (SMEs). This suggests that when Malaysian manufacturing companies recognise the benefits of Quality 4.0 technologies such as improved efficiency, enhanced product quality, and increased competitiveness, they are more likely to adopt them.

Further supporting this, Escobar et al. (2021) highlights how Quality 4.0 adoption, driven by big data and AI, can significantly improve product quality by enabling more accurate process monitoring and control. The ability to consistently produce high-quality products is a compelling relative advantage that encourages adoption among Malaysian manufacturing companies.

Organisations that recognise the strategic value of digital data in the context of Quality 4.0 are poised to gain a competitive advantage, particularly through enhanced customer satisfaction and optimised product life cycle management. By utilising data-driven insights, businesses can refine their product and service designs, ensuring they meet the evolving needs of their customers (Sony et al., 2020, 2021). Quality 4.0 technologies, with their inherent focus on data, transform decision-making processes in manufacturing environments. Through the integration of big data analytics, companies can uncover patterns in production processes, gain deeper understanding of customer preferences, and identify areas that require improvement. This enhanced decision-making ability becomes a significant source of relative advantage, compelling organisations to adopt Quality 4.0. The potential for improved strategic decision making through the alignment of quality management practices with Industry 4.0 technologies is a key theme explored by Liu et al. (2023). They argue that leveraging these advanced technologies not only strengthens the decision-making framework but also enhances organisational competitiveness. In short, companies that can harness the power of data-driven insights within Quality 4.0 are better positioned to navigate market complexities and maintain a leading edge in their respective industries.

Therefore, the following hypothesis is developed based on above arguments:

H1: Relative advantage of Quality 4.0 technologies is positively and significantly related to Quality 4.0 adoption.

2.8.2 Artificial Intelligence (AI) Compatibility and Quality 4.0 Adoption

Among the applications of AI as Quality 4.0 tools include language processing, navigations, computer vision, chatbots, robotics, personal assistants, and making complex decisions in which machine learning, neural networks and deep learning made up some of the domain of AI in Quality 4.0 tools ecosystem (Radziwill, 2018). Handling of big data plays the most important role in quality management and the integration of AI into the processing of data collection, analysis, and decision-making will shift the quality performance monitoring to the next level (El Jaouhari et al., 2024; Escobar, Cantoral-Ceballos, et al., 2024; Escobar, Macias-Arregoyta, et al., 2024; Hoffmann & Reich, 2023; Sony et al., 2020; Zulqarnain et al., 2022).

The new Industrial AI survey report published by US Manufacturing Leadership Council in 2023 revealed that manufacturing and production are in the top list of functions adopting AI in the organisation, followed by inventory management, R&D, and quality operations (Brousel et al., 2023). Despite its pervasive promise, the status of AI adoption only started entering new wave of adoption in manufacturing industry after breakthrough observed in AI products led by Open AI's ChatGPT. Based on the survey, 57% of the manufacturing companies are still piloting and experimenting with AI technology to find the best compatibility in existing platforms and the impact for their current operational strategies and future business model (Brousel et al., 2023).

A study carried out by Badghish and Soomro (2024) revealed that AI compatibility with existing setup of the companies plays a significant role in its adoption. Another study carried out by Russo (2024) also indicated that the compatibility of AI tools within existing business workflows of companies predominantly drives their adoption. Hence, compatibility of AI integration to existing data management platforms would be crucial and we may expect positive correlation between both variables in this hypothesis testing.

The following hypothesis is developed based on above arguments:

H2: AI compatibility is positively and significantly related to Quality 4.0 adoption.

2.8.3 Top Management Support and Quality 4.0 Adoption

Top management support is crucial in driving the successful implementation of quality management initiatives, especially with the adoption of Quality 4.0, which often necessitates significant shifts in organisational structure and business processes (Sony et al., 2021). The importance of top management support in championing digital transformation becomes even more prominent in Quality 4.0 adoption, as top management's visibility and commitment can significantly influence employee's willingness to embrace these changes (Sony et al., 2020).

Research by Sony et al. (2021) revealed top management support is indispensable for the successful integration of Quality 4.0 practices. Their studies emphasised that top management commitment in providing necessary resources, establishing clear strategic objectives, and fostering a culture conducive to digital transformation within quality management. This notion is echoed in the findings of Antony, Sony, et al. (2023), who identified top management support as one of the critical factors in organisational readiness for adopting Quality 4.0. Their research suggests that top management's commitment is vital in mitigating resistance to change and ensuring the smooth adoption of new technologies and practices.

Further supporting this view, Maganga and Taifa (2023) also highlighted the importance of top management support as one of the key enablers for adopting Quality 4.0 in manufacturing industries. Similarly, Zulfiqar et al. (2023) empirically confirmed that top management support was recognised as one of the primary factors in assessing an organisation's readiness for Quality 4.0. In all, these studies collectively stress the importance of top management's active involvement in the successful transition to Quality 4.0, confirming its role as a driving force in overcoming obstacles and facilitating organisational change.

Hence, the following hypothesis is developed based on above arguments:

H3: Top management support is positively and significantly related to Quality 4.0 adoption.

2.8.4 Transformational Leadership and Quality 4.0 Adoption

Adopting Quality 4.0 represents a fundamental shift in business processes, making effective leadership a key factor in facilitating the transition. Transformational leadership known for its emphasis on innovation, learning, and change, is particularly relevant for companies navigating the complexities of Quality 4.0 adoption (Sony et al., 2020). The process of adopting Quality 4.0 requires not only organisational readiness, but also leadership commitment and direction, positioning transformational leadership as a relevant organisational capability in supporting such initiatives. Research consistently underscores the importance of leadership in driving the successful implementation of Quality 4.0 and its alignment with corporate sustainability performance. Numerous studies highlighted the positive relationship between management leadership and the successful integration of Quality 4.0 (Antony, Swarnakar, et al., 2023; Glogovac et al., 2023; Guzmán et al., 2020; Kelly, 2019; Oberer & Erkollar, 2018). Companies with visionary leaders, committed to digital transformation, and fostering a culture of learning and development, are better positioned to adopt and thrive in Quality 4.0 framework (Sony et al., 2020, 2021).

Specifically, a study by Laohavichien et al. (2009) explored the influence of transformational leadership on quality improvement efforts. The results indicated a positive relationship between transformational leadership and quality management practices. Transformational leaders are often able to inspire continuous improvement and innovation, which are relevant for organisations pursuing Quality 4.0. This leadership style may provide the necessary strategic direction and vision to align organisations with Industry 4.0's digital advancements, ultimately positioning them for sustained competitive advantage.

In addition, Virmani et al. (2024) emphasised the role of transformational leadership in addressing barriers associated with Quality 4.0 adoption. Their research revealed that transformational leaders, through their visionary guidance and ability to inspire change can support organisations in navigating implementation challenges. Collectively, these studies provide a theoretical basis for examining the relationship between transformational leadership and Quality 4.0 adoption. Thus, we may expect a positive correlation in the hypothesis mentioned earlier.

The following hypothesis is developed based on above arguments:

H4: Transformational leadership is positively and significantly related to Quality 4.0 adoption.

2.8.5 Organisational Culture and Quality 4.0 Adoption

Research indicates that to achieve corporate sustainability goals under the setting of Quality 4.0, companies and their members must adopt a new culture that prioritises transparency, connectivity, collaboration, and insights, utilizing tools to facilitate rapid and effective decision making in quality management (Sony et al., 2021). Quality 4.0 facilitates the vertical, horizontal, and end-to-end integration of manufacturing quality management systems. As a result, an organisational culture that prioritises learning, trust, collaboration, and cross-functional cooperation across different units is essential (Mohelska & Sokolova, 2018; Stock & Seliger, 2016) and as key enabler of effective

Quality 4.0 adoption (Antony, Swarnakar, et al., 2023; Swarnakar et al., 2023; Zulfiqar et al., 2023).

A study by Sony et al. (2021) identified organisational culture as pivotal readiness factor for Quality 4.0 adoption. The research highlights that a culture fostering innovation, continuous improvement, and openness to change significantly enhances an organisation's preparedness for Quality 4.0. Conversely, cultures resistant to change or lacking in collaborative practices can impede the successful implementation of Quality 4.0 initiatives.

Further supporting this, Antony, Sony, et al. (2023) in their intercontinental study also identified organisational culture as one of the top three factors for successful Quality 4.0 adoption. The study emphasises that a culture promoting learning, adaptability, and employee engagement is crucial for overcoming barriers to Quality 4.0 implementation.

Additionally, the empirical investigation by Zulfiqar et al. (2023) underscores the importance of organisational culture in Quality 4.0 readiness. The study presents a readiness assessment tool and finds the companies with a culture emphasizing innovation, employee involvement, and proactive change management are better positioned to implement Quality 4.0 practices effectively.

Therefore, the following hypothesis is developed based on above arguments:

H5: Organisational culture is positively and significantly related to Quality 4.0 adoption.

2.8.6 External Support and Quality 4.0 Adoption

Quality 4.0 is a complex concept with several dimensions, and comprehending emerging technology is inherently demanding especially at the early adoption stage. Therefore, obtaining assistance from various parties can play a vital role in the successful adoption of Quality 4.0 to attain corporate sustainability goals in technology aspect (Jayashree et al., 2022; Masood & Egger, 2019). Examples of such external support may involve engaging consultancy firms or industry associations, seeking assistance from vendors or peers in the same or different sectors, and leveraging established industrial standard or best practices for insights (Gangwar, 2018; Maduku et al., 2016; Masood &

Egger, 2019). Accessing external support from various sources can help mitigate the challenges associated with a lack of knowledge about new technology.

A study carried out by Jayashree et al. (2022) identified external support as a significant determinant in the successful implementation of Industry 4.0 technologies. The findings indicate that external support, including governmental incentives, industry collaborations, and support from technology vendors, plays a crucial role in facilitating the adoption process. This support helps companies overcome barriers such as financial expertise, lack of expertise, and resistance to change, thereby enhancing their readiness and capability to implement Industry 4.0 technologies.

Further supporting this view, Khin and Kee (2022) identified external support as a facilitating factor in the adoption of Industry 4.0 technologies, The research highlighted that resources, skills, and support provided by external entities are instrumental in aiding companies to embrace new technologies. The study also emphasised that external support could mitigate challenges such as lack of funding, insufficient knowledge, and technical difficulties, which are common barriers to innovation adoption.

These findings are highly relevant to Quality 4.0 adoption, as its successful implementation relies on leveraging emerging tools and advanced technologies from Industry 4.0 to enhance quality management processes.

Hence, the hypothesis below is proposed to examine the observations.

H6: External support is positively and significantly related to Quality 4.0 adoption.

2.8.7 Market Pressure and Quality 4.0 Adoption

Academics have suggested that the adoption of technology is more likely to occur when there is market pressure, particularly in the setting of Quality 4.0 adoption where companies focus on satisfying their customers will adjust their strategies accordingly including the whole value chain management (Jia et al., 2017; Maduku et al., 2016; Sony et al., 2021). When companies experience greater market pressure, they tend to be more inclined to adopt new technology as a method of enhancing their competitive edge and promoting corporate sustainability (Jayashree et al., 2022).

Market pressure is a key driver of Quality 4.0 adoption in Malaysian manufacturing companies, as companies must respond to increasing demands from various external forces. A study carried out by Fadilasari et al. (2024) emphasised that market pressures such as the need to stay competitive and meet customer demands drive companies to adopt Quality 4.0 despite facing significant barriers. The findings suggest that strategic focus on overcoming these barriers is essential for successful Quality 4.0 implementation, providing a roadmap for companies striving for excellence in the digital era. On the other hand, Mahin et al. (2024) examined the role of market pressures especially increasing customer requirements, which necessitate rigorous monitoring of production processes to avoid errors and deviations.

According to Min and Kim (2024), businesses are increasingly adopting artificial intelligence and digital transformation technologies to optimise network operations and enhance overall efficiency, driven by the need to remain competitive in rapidly evolving markets. Similarly, Badghish and Soomro (2024) highlight that enterprises adopt AI technologies to improve corporate sustainable performance, influenced by external pressures such as market competition and regulatory compliance. These studies indicate that companies facing intense market pressure are more likely to integrate Quality 4.0 technologies, such as AI-driven quality management systems and predictive analytics, to maintain competitiveness and meet industry expectations.

Therefore, the above hypothesis is formulated based on the preceding discussion.

H7: Market pressure is positively and significantly related to Quality 4.0 adoption.

2.8.8 Quality 4.0 Adoption and Economic Sustainability

The adoption of Quality 4.0 offers a range of economic benefits, as concluded by Antony, Sony, et al. (2022), who highlighted significant improvements in total revenue, cost reductions related to quality, and enhanced conformance and performance quality, all of which contribute to economic sustainability. Additionally, Antony, Swarnakar, et al. (2023) supports the view that early adopters of Quality 4.0 have realised numerous advantages, including boosted revenue, enhanced competitive positioning, higher profit margins, reduced sales costs, improved stock prices, lower inventory and material costs, minimised waste, and a decrease in failure-related expenses.

Looking ahead, the long-term financial rewards for implementing Quality 4.0 are promising for manufacturing organisations. Achieving these gains involves leveraging responsive and agile manufacturing systems (Sony & Naik, 2020), optimising mass customisation to meet customer demands more effectively (Park et al., 2017), and ensuring better quality control through manufacturing automation (Sony et al., 2020). Further benefits include the use of artificial intelligence (AI) for enhanced customer relationship management (Libai et al., 2020) and effective inventory management. The potential economic advantages of adopting Quality 4.0 are manifold, encompassing increased revenue, reduced cost of quality, and superior product quality, all of which support the drive towards economic sustainability in manufacturing operations (Antony, Sony, et al., 2022). These findings underscore the value of embracing digital transformation in quality management, positioning organisations for long-term profitability and operational excellence.

Hence, the above hypothesis is formulated based on the preceding discussion.

H8: Quality 4.0 adoption is positively and significantly related to economic sustainability.

2.8.9 Quality 4.0 Adoption and Environmental Sustainability

Early adopters of Quality 4.0 have gained a distinct edge over late adopters, particularly in the realm of environmental sustainability. These companies benefit from enhanced resource efficiency, significantly reducing environmental impacts by minimising waste, scrap, and rework. This technological advancement not only helps organisations comply with environmental regulations but also optimises the consumption of raw materials, improving overall system efficiency. Moreover, Quality 4.0 facilitates the secure collection and real-time sharing of environmental management data, ensuring more effective resources use while also boosting the company’s reputation and customer loyalty. Real-time monitoring of environmental metrics further enhances these benefits (Antony, Swarnakar, et al., 2023).

At its core, Quality 4.0 drives the pursuit of resources efficiencies, which is one of the primary catalysts for achieving environmental sustainability. By enabling continuous digital monitoring of every subprocess within the manufacturing cycle, it effectively curtails waste, scrap, and rework (Küpper et al., 2019). This ongoing digital transformation across the entire resource life cycle is pivotal in reducing environmental impact, particularly by minimising emissions and conserving valuable resources like raw materials, energy, and water (Oláh et al., 2020). Quality 4.0 aligns with sustainability's "ten Rs" framework, which consists of recovery, recycling, remanufacturing, refurbishing, repairing, reusing, reducing, rethinking, and refusing. It stands as a complementary framework, advancing these principles and supporting cleaner production processes (Bag et al., 2021). Additionally, Antony, Sony, et al. (2022) also discovered that Quality 4.0 adoption leads to reduction in scrap, waste, and rework, while optimising resource utilisation, thereby enhancing the environmental sustainability of manufacturing companies.

In short, the adoption of Quality 4.0 offers compelling environmental benefits, directly supporting resource conservation, waste reduction, and the overall advancement of sustainable practices within the manufacturing sector. This approach not only promotes compliance with environmental standards but also solidifies the organisation's standing as a responsible corporate entity committed to environmental sustainability.

Hence, the above hypothesis is formulated based on the preceding discussion.

H9: Quality 4.0 adoption is positively and significantly related to environmental sustainability.

2.8.10 Quality 4.0 Adoption and Social Sustainability

Quality 4.0 significantly enhances the social dimensions of both internal and external stakeholders by delivering high-quality products and services, often with superior safety features (Sony et al., 2021). Quality 4.0 also transitions society toward a more knowledge-driven era through the development of digital skills (Sony & Aithal, 2020). As manufacturing outputs experiences substantial growth due to the integration of Quality 4.0, society stands to benefit in the long term through lower costs of products and services, which ultimately boosts overall economic efficiency (Küpper et al., 2019).

Moreover, Antony, Sony, et al. (2022) also noted that the adoption of Quality 4.0 positively impacts employees' work-life quality, fostering the production of high-quality, cost-effective products, while improving workplace conditions.

The social sustainability of organisations is also strengthened by Quality 4.0, as evidenced by Antony, Swarnakar, et al. (2023). Their study revealed that early adopters of Quality 4.0 experience significant improvements in worker health and safety, reducing accidents, and enhancing overall working environments. Furthermore, the implementation of Quality 4.0 generates new job opportunities in areas such as system safety and process engineering. It also encourages the creation of a more transparent and digitalised human resources process, helping to mitigate workplace favouritism, politics, and repetitive, hazardous tasks. This result is not only an improved work environment but also boosts the broader social fabric by enhancing digital literacy, improving living standards, and fostering socioeconomic growth. This transformation promotes job creation, addresses human resource challenges, and contributes to societal well-being (Antony, Swarnakar, et al., 2023).

In conclusion, Quality 4.0 goes beyond its operational benefits, offering tangible social improvements by enhancing workplace conditions, fostering skill development, and contributing to the broader social and economic upliftment. It plays an important role in shaping sustainable, digitally proficient workforce and promoting social equity.

Hence, the above hypothesis is formulated based on the preceding discussion.

H10: Quality 4.0 adoption is positively and significantly related to social sustainability.

2.9 Chapter Summary

Chapter 2 delves into a comprehensive review of existing literature addressing the adoption of Quality 4.0 and its impact on corporate sustainability performance. The chapter begins by tracing the evolution of Total Quality Management (TQM) and its transformation into Quality 4.0, which incorporates advanced Industry 4.0 technologies. These innovations serve to elevate quality management practices to new heights, enabling organisations to enhance efficiency, productivity, and decision-making processes.

A significant portion of the chapter is dedicated to exploring key theoretical frameworks that underpin the adoption of Quality 4.0. The Technology-Organization-Environment (TOE) framework is selected as the primary underpinning theory for understanding how and why organisations adopt new innovations, including Quality 4.0. In addition, the chapter integrates Resource-Based View (RBV) theory, which offers a foundational perspective for understanding how the adoption of Quality 4.0 can serve as a strategic resource and capability that can enhance corporate sustainability performance across TBL dimensions.

Building on the insights from the literature, the chapter proposes a conceptual framework that aligns the Quality 4.0 adoption based on TOE dimensions with corporate sustainability performance. Several hypotheses are introduced, suggesting that technological, organisational, and environmental factors positively influence the adoption of Quality 4.0. Furthermore, it is posited that the adoption of Quality 4.0 will have a favourable impact on corporate sustainability performance.

The chapter also identifies several research gaps, including the absence of a universally recognised framework for Quality 4.0 adoption, the disconnect between theoretical models and practical applications, and the lack of empirical studies, particularly within the context of Malaysian manufacturing companies. To address these gaps, this study aims to empirically validate the relationships between the adoption of Quality 4.0 and corporate sustainability performance, providing a novel contribution to the literature, especially within the Malaysian manufacturing sector.

In summary, this chapter sets the foundation for the study by reviewing the theoretical underpinnings and establishing a conceptual framework to guide the investigation of Quality 4.0's role in advancing corporate sustainability. Through its focus on both theoretical exploration and practical application, it seeks to provide valuable insights into how Quality 4.0 can drive corporate sustainability performance in modern manufacturing practices.

CHAPTER 3:

RESEARCH METHODOLOGY

3.1 Introduction

Chapter 3 begins with an introduction that outlines the research design, populations and sampling procedures, instrument development, data collection procedure, data tabulation and testing methodology, and types of data analysis to be carried out using SmartPLS statistical software. This chapter aims to portray a thorough description of the methods and procedures deployed in this study, ensuring a structured and systematic approach to the research.

3.2 Research Design

This research adopts a quantitative research design to address the research gaps identified in previous studies. A cross-sectional survey questionnaire approach is proposed to be utilised in this study to examine the relationship between independent and dependent variables within the proposed conceptual framework. Additionally, this research follows a deductive approach, where a conceptual framework is developed and tested through empirical observation, allowing general principles to be applied to specific instances. A cross-sectional design is particularly suitable when time and resource constraints limit the feasibility of a longitudinal study. This method captures a snapshot, offering insights into the phenomenon within a defined timeframe (Ahmad & Bujang, 2022).

According to Creswell (2012), quantitative design is adopted by researchers to address a research problem by describing trends or explaining the relationship among variables, aligning with the objectives of this research. Quantitative research is also widely used since mid-13th century in natural and social sciences driven by the needs of researchers for data quantification, especially seeking for structured, numerical or statistical data analysis and interpretation (Mohajan, 2020).

The research in the field of Quality 4.0 has been getting momentum in recent years, and quantitative research is suitable to comprehend key factors towards adoption of Quality 4.0 in contributing to enhancing corporate sustainability performance within this research context. The strength of quantitative research using survey questionnaire is tally with the needs of this study in terms of its ability to reduce development time, economical, broad reach, highly representative and minimise researcher's bias (Queirós et al., 2017).

3.3 Research Sample Size

This study defines the unit of analysis at the organisational level. The target population for this study consists of manufacturing companies across Malaysia's thirteen states and one federal territory. These companies were selected form those registered under the Federation of Malaysian Manufacturers (FMM, 2022). Figure 3-1 presents a summary of the distribution of manufacturing companies across Malaysia. There are 3, 123 manufacturing companies registered as Manufacturer under FMM Business Type in 2022 directory as initial target population. The sampling frame was then filtered for companies with more than 75 employees, representing medium and large manufacturing companies. This criterion defines the sampling frame because such companies are more likely to be Quality 4.0 early adopters within the manufacturing sector (Wawak et al., 2023). This has reduced the eligible population to 1, 630 companies based on preliminary FMM database screening.

From this sampling frame, systematic random sampling was employed. According to Ahmad and Bujang (2022), the systematic sampling procedure ensures that each element in the population has equal change of selection. This is done by dividing the total population by the sample size to determine a sampling interval, ensuring a structured and unbiased selection process.

In this study, a sampling unit was picked at regular intervals (every *3rd* element from the sampling frame) using systematic random sampling method. A structured questionnaire was distributed to the targeted population with respondents confined to senior level quality professionals within the organisation as key informants to acquire the information needed in the study.

To further refine respondent eligibility, two additional criteria were established. First, respondents were required to have a minimum of one year of working experience as a senior quality professional in their current manufacturing company. Second, the manufacturing company itself must have adopted Quality 4.0 and been in operation for at least one year. These conditions ensured that the data were obtained from experience professionals embedded in manufacturing companies actively adopting Quality 4.0 initiatives and practices.

In determining the appropriate samples size, two guidelines were applied. The first one is the 10-times rules of thumb. According to Hair et al. (2022), this guideline states that the minimum sample size should be at least ten times the number of independent variables in the most complex regression within the PLS path model. This applies to both the measurement and structural models. Practically, it means taking ten times the maximum number of arrowheads pointing at any latent variable in the model. In this study, applying this rule yields a required sample size of 7 x 10 = 70 observations.

To ensure a more reliable minimum samples size, second guideline of applying statistical power analyses using G*Power software (version 3.1.9.7) was used in this study, considering factors such as effect size, alpha level, statistical power, and the number of predictors, with a 95% confidence level and a 5% margin of error (Cohen, 1988; Faul et al., 2007). The proposed conceptual framework includes eight predictors, requiring a minimum sample size of 109 with the required input parameters as illustrated in Figure 3-2 (Ali & Johl, 2022).

To compensate for the typical response rate of survey which ranges from 20 to 30% (Easterby-Smith et al., 2015; Jayashree et al., 2022), additional questionnaires of up to 550 sets as a minimum will need to be sent out. Every 3rd company in the sampling frame of 1, 630 companies was systematically selected, using a 1-2-3 sequence to determine inclusion. If the first round of systematic random sampling does not yield an adequate response rate, the process will be repeated in a second and, if required, a third round. Repeating systematic random sampling ensures consistency and preserves representatives across the sampling frame.

Figure 3-1:
Manufacturing Companies Registered under FMM

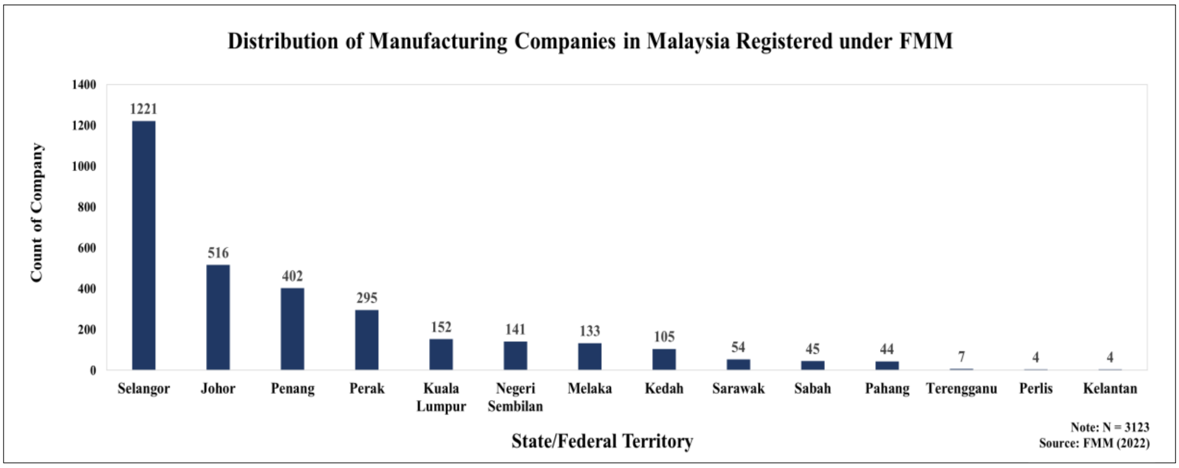
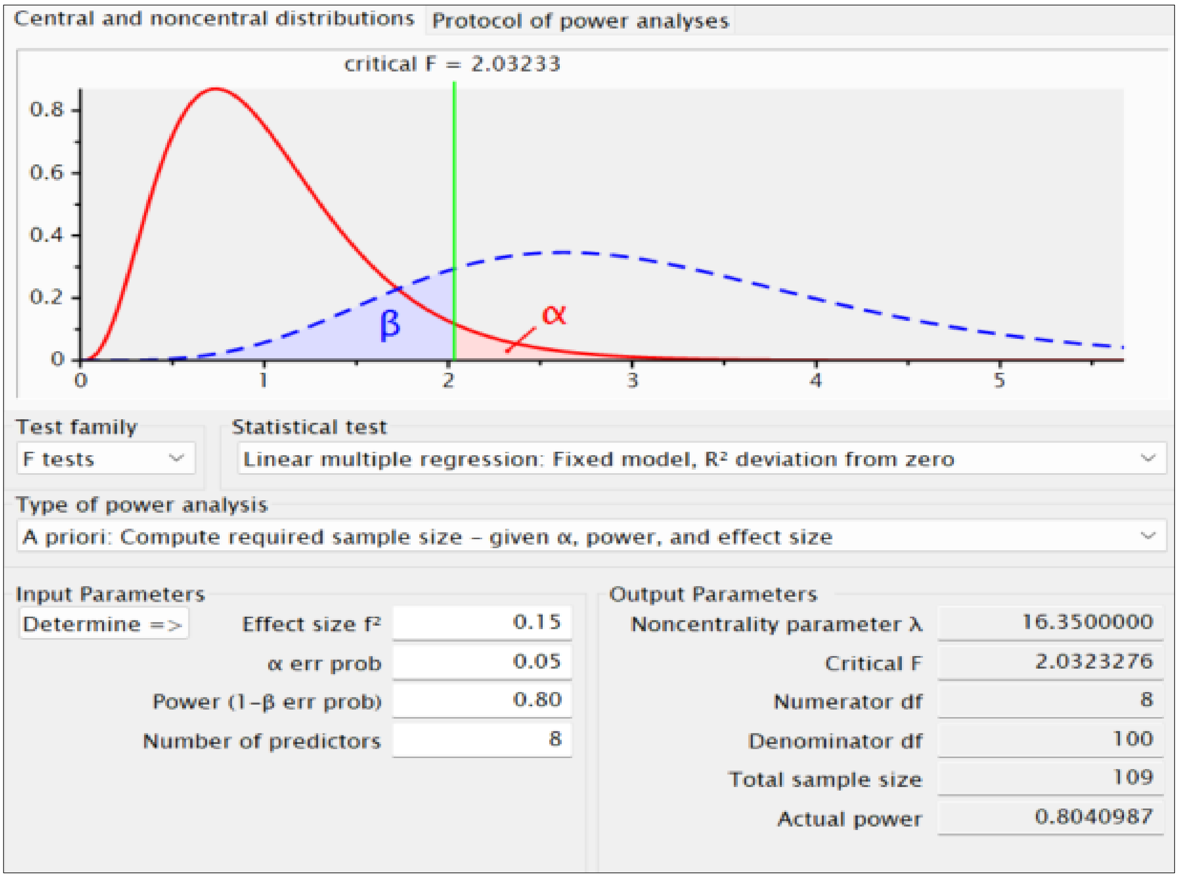


Figure 3-2:
G*Power Sample Size Determination



Note: Effect size = 0.15; Power = 0.80; α = 0.05 (Ali & Johl, 2022)

3.4 Development of Research Questionnaire

The questionnaire was designed in English, and a cover letter was attached as an introduction to explain the purpose of survey to the participants. The questionnaire was organised into three main sections and six subsections.

This study captured respondent's demographic information in first subsection which consists of 7 items, covering gender, job position, years of service, type of manufacturing business, business location, duration of operation and workforce size. Second subsection consists of 8 items to measure technological context. Subsection three consists of 13 items to measure organisational context. Subsection 4 comprises of 14 items to measure environmental context. Subsection 5 consists of 5 items to measure Quality 4.0 adoption. Subsection 6 comprises 27 items to assess corporate sustainability performance, in which 11 items measure economic sustainability, 7 items measure environmental sustainability, and 9 items measure social sustainability.

Appendix 1 depicts the cover letter, and questionnaire constructs in English version as additional reference. This study derived measurement items from established research and modified them to fit the study context. These adaptations are summarised and tabulated in Table 3-1.

Table 3-1:
Constructs and Items Sources

Sub Section	Construct	Dimension	Number of Items	Sources	Rating Scale
1	Demographic Information	-	7	Self-developed	-
2	Technological Context	Relative Advantage (RA)	4	Premkumar & Roberts (1999)	Strongly disagree (1) and strongly agree (7)
		AI Compatibility (AC)	4	Rogers (2003), as cited in Teo & Pian (2003)	Strongly disagree (1) and strongly agree (7)
3	Organisational Context	Top Management Support (TS)	4	Premkumar & Roberts (1999), as cited in Lian et al. (2014)	Strongly disagree (1) and strongly agree (7)
		Transformational Leadership (TL)	5	Podsakoff et al. (1996), as cited in García-Morales et al. (2008)	Strongly disagree (1) and strongly agree (7)
		Organisational Culture (OC)	4	Ahn & Ahn (2020)	Strongly disagree (1) and strongly agree (7)
4	Environmental Context	External Support (ES)	7	Premkumar & Roberts (1999) and Masood & Egger (2019), as cited in Jayashree et al. (2022)	Strongly disagree (1) and strongly agree (7)
		Market Pressure (MP)	7	Ghobakhloo et al. (2011) and Maduku et al. (2016), as cited in	Strongly disagree (1) and strongly agree (7)

Sub Section	Construct	Dimension	Number of Items	Sources	Rating Scale
				Jayashree et al. (2022)	
5	Quality 4.0 Adoption	-	5	Jayashree et al. (2022)	Strongly disagree (1) and strongly agree (7)
6	Corporate Sustainability Performance	Economic Sustainability (ECS)	11	Nasir et al. (2022)	Strongly disagree (1) and strongly agree (5)
		Environmental Sustainability (EVS)	7	Nasir et al. (2022)	Strongly disagree (1) and strongly agree (5)
		Social Sustainability (SS)	9	Nasir et al. (2022)	Strongly disagree (1) and strongly agree (5)

3.5 Measures

Quality 4.0 adoption and corporate sustainability performance were evaluated based on measurement items adapted from prior research. Responses from Quality 4.0 adoption were recorded using a 7-point Likert Scale, ranging from strongly disagree (1) to strongly agree (7). Meanwhile, corporate sustainability performance was evaluated using a 5-point Likert scale, spanning from strongly disagree (1) to strongly agree (5). The detailed operationalisation and measurement of these constructs are presented in the subsequent sections.

3.5.1 Demographic Information

Seven self-developed demographic questions which include gender, current position of respondents in the company, duration of service in current company, type of manufacturing business, business location, length of operation and workforce size were included in the first section of the questionnaire.

3.5.2 Technological Context

3.5.2.1 Relative Advantage

Relative advantage was evaluated using four items derived from Premkumar and Roberts (1999). These items are designed to capture the organisation's perception of the benefits brought by the adoption of Quality 4.0 technologies.

3.5.2.2 AI Compatibility

AI compatibility was measured with four items adapted from Teo and Pian (2003) with original items developed by Rogers (2003). It will measure the compatibility of AI integration in Quality 4.0 adoption as compared to the organisation's existing beliefs, values systems, work practices, and technology environment. Notably, Teo and Pian (2003) operationalised compatibility specifically within a technology adoption context, arguing that the feasibility of new technology integration is dependent on its compatibility with an organisation's existing technological infrastructure as well as technology-related cultural values, an approach this research adopts by explicitly capturing the technical challenge of integrating AI with existing information technology infrastructure.

3.5.2.3 Top Management Support

Four items adapted from Lian et al. (2014) were used to measure the commitment of top management support to Quality 4.0 adoption, originally developed by Premkumar and Roberts (1999). These items will gauge the extent of top management support in driving the adoption of Quality 4.0 in the organisation.

3.5.2.4 Transformational Leadership

Five items modified from García-Morales et al. (2008), with original items developed by Podsakoff et al. (1996) were utilised to evaluate transformation leadership influence on Quality 4.0 adoption. These items will gauge how respondents perceive transformational leadership within their organisation and the influence of this leadership style has on fostering the adoption of Quality 4.0.

3.5.2.5 Organisational Culture

Four items adapted from Ahn and Ahn (2020) were used to assess the influence of organisational culture on Quality 4.0 adoption. These items are designed to capture the extent to which organisational culture shapes the adoption of Quality 4.0 within the organisation.

3.5.3 Environmental Context

3.5.3.1 External Support

Seven items modified from Jayashree et al. (2022), initially introduced by Premkumar and Roberts (1999) and Masood and Egger (2019) were selected to assess external support influence on Quality 4.0 adoption. This assessment focuses on evaluating the availability and accessibility of vendors, the relevance of Quality 4.0 solutions within the current industrial context, and the extent of technical assistance, consultation, and training provided by these vendors.

3.5.3.2 Market Pressure

Seven items modified from Jayashree et al. (2022) which were originally used by Ghobakhloo et al. (2011) and Maduku et al. (2016) were selected to measure market pressure influence on Quality 4.0 adoption. This will gauge the extent of market pressure influencing the organisation's decision to adopt Quality 4.0, considering factors such as demands from suppliers, expectations from customers, competitive pressures, and the overall dynamics of the industry environment.

3.5.4 Quality 4.0 Adoption

Five items modified from Jayashree et al. (2022) were used to measure the Quality 4.0 adoption. Respondents were asked to evaluate the benefits they have gained from adopting Quality 4.0, including improvements in revenue generation, resource management, and manufacturing efficiency. Additionally, the effectiveness of Quality 4.0 adoption and how it aligns and integrates with the current structure of the organisation were assessed.

3.5.5 Corporate Sustainability Performance

3.5.5.1 Economic Sustainability

Economic sustainability was measured with eleven items adapted from Nasir et al. (2022). Respondents were asked to capture the economic benefit derived from Quality 4.0 adoption such as revenue growth, profit growth, sales growth, reputation, customer base expansion, product quality improvement, customer complaint reduction, inventory cost reduction, productivity improvement, delivery lead time reduction, and new product development.

3.5.5.2 Environmental Sustainability

Environmental sustainability was measured with seven items adapted from Nasir et al. (2022). Respondents were asked to acknowledge the environmental benefit derived from Quality 4.0 adoption such as waste reduction, reduction of material usage, energy consumption reduction, noise reduction, and alignment with organisational emission policies.

3.5.5.3 Social Sustainability

Social sustainability was measured with nine items adapted from Nasir et al. (2022). Respondents were asked to reflect on the social benefit derived from Quality 4.0 adoption such as training and skill development, corporate social investment, product image, employee satisfaction, customer satisfaction, supplier base expansion and occupational health and safety of employees.

3.6 Pre-Test

This study used primary data as the main source of information. Before actual data collection was carried out, face validity and content validity through three experts in quality management were conducted as pre-test. This instrument validation step was recommended by Memon et al. (2023). Face validity ensures that the questionnaire items are clear, appropriate, logically connected, and properly formatted. Content validity, on the other hand, verifies that the items are relevant, comprehensive, and represent the intended constructs. Table 3-2 summarises the feedback received from experts, and the questionnaire was then refined by improving the clarity of question phrasing and eliminating unreliable or redundant items. One of the industrial experts also filled up the questionnaire via Google Forms, the platform selected for this study. The test produced satisfactory feedback, confirming the suitability of both the instrument and the platform for full-scale deployment.

Although pre-testing with actual respondents was not feasible due to limited access to senior quality professionals and the need to preserve the target pool for full survey deployment, the instrument went through rigorous validation through expert review. A panel comprising of one academic expert and two industrial experts ensured both theoretical and practical relevance, and iterative refinements were made to enhance clarity and eliminate unreliable items or redundancy. Additionally, a simple pre-test was conducted with one industrial expert via Google Forms to confirm usability on the selected data collection platform.

While this approach does not replace respondent-based pre-testing and pilot tests, it represents a widely accepted alternative in organisational research when resources are scarce (Boateng et al., 2018). Besides, it is also important to note that this study does not develop a new instrument. Instead, it adapts items from established and previously validated survey questionnaires. The role of the pre-test was not to establish construct validity from scratch, but to ensure that the adapted instrument was contextually appropriate, clearly worded, and practically feasible for the target respondents in Malaysian manufacturing companies. Instrument reliability and validity were further confirmed through post-hoc statistical analyses.

Table 3-2:
Outcomes of Pre-Test

Sub Section	Question	Expert 1	Expert 2	Expert 3	Comments/ Amendments
RA	***RA2:*** Quality 4.0 technology will allow us to cut costs in our operations.		You might want to consider replacing "cut cost" with "reduce overall operation costs" or "improve operations efficiencies – reducing cost &/or lead time or cycle time etc.		Quality 4.0 technology will allow us to ***reduce overall operation costs.***
	RA4: Adoption of Quality 4.0 technology will provide timely information for decision making.		You might want to consider adding timely and more accurate/ reliable information.		Adoption of Quality 4.0 technology will provide timely ***and more accurate*** information for decision making.
MP	***MP1:*** Current industrial setting is pressuring us to adopt Quality 4.0.	Not specific. Please define what are the industry settings.			Current ***manufacturing*** industrial setting is pressuring us to adopt Quality 4.0.
	MP7: Adopting Quality 4.0 helps us to compete better with our competitors.	Maybe change to "competitive" rather than "compete better with our competitors".			Adopting Quality 4.0 ***enhances our competitiveness in the market.***
EVS	***EVS6:*** The adoption of Quality 4.0 increases public health and safety			Health and safety could be under social.	***Remove this item from Environmental Sustainability.***
SS	***SS3:*** The adoption of Quality 4.0 improves product image.		Product image – can consider substitute with Product quality perception/ branding		The adoption of Quality 4.0 improves product ***branding.***

3.7 Data Collection Procedure

Data was collected from the samples of Malaysia manufacturing companies using Google Forms, as a platform for online survey. To ensure the online data is conducted effectively, the following procedures were implemented. First, companies selected from the first round of systematic random sampling criteria was contacted via email or messaging, using contact details sourced from the Federation of Malaysian Manufacturers (FMM) database. The survey link was embedded in the email invitation with cover letter, outlining the research context and its significance.

The survey was self-administered by the respondent and was closely monitored by the researcher to improve the survey questionnaire response rate. Few procedure remedies as recommended by past studies were applied to minimise the risk of common method bias (CMB), which include developing a survey using different scale types such as 5-point and 7-point Likert scales and with different anchors (Memon et al., 2023), clarifying research purpose and instructions via a cover letter, assuring respondent's anonymity and confidentiality of the study and the proposed used of the survey data (Jordan & Troth, 2020; Memon et al., 2023; Podsakoff et al., 2024).

A total of 1,600 questionnaires were distributed over three rounds of systematic random sampling, as the initial round yielded a low response rate. After an eleven-week data collection period, supported by two additional email follow-ups and several messaging reminders, 127 complete questionnaires were returned, resulting in an overall response rate of 8%. This response rate was considered acceptable, as the number of complete questionnaires exceeded the minimum sample size requirement of 109 based on G*Power calculation as specified in Section 3.3.

3.8 Methodological Considerations

Although the overall response rate was relatively low, recent methodological evidence indicates that low response rates are a systematic characteristic of organisational level survey research, particularly when studies require company level data from senior respondents. Holtom et al. (2022) reported that organisational level surveys consistently achieve lower response rates than individual level studies due to executive time constraints and the sensitivity of organisational information. In addition, contemporary methodological guidance emphasises the importance of considering transparent justification of sampling decisions, contextual constraints, and adequate statistical power alongside response rates when assessing survey quality (Memon et al., 2023). Nevertheless, the possibility of non-response bias cannot be fully eliminated and is therefore acknowledged as a methodological consideration.

This study adopted a single key-informat design, drawing insights from senior quality professionals to report on organisational level constructs such as Quality 4.0 adoption and corporate sustainability performance. While this approach is widely used in organisational and technology adoption research where constructs are strategic and cross-functional in nature, it may be associated with perceptual bias and common method bias (Jordan & Troth, 2020; Podsakoff et al., 2024). To mitigate these risks, procedural remedies including varied scale formats, clear construct separation, and assurances of anonymity and confidentiality were implemented. In addition, post hoc statistical assessments, including Harman's single factor test and the full collinearity variance inflation factor (FVIF) approach were conducted to assess the potential presence of common method bias.

It is also acknowledged that this study did not include a respondent-based pilot test, thereby limiting the opportunity to observe actual response behaviour, interpretive nuances, and context-specific comprehension among the intended respondent group prior to full deployment. While expert review and limited platform testing supported item clarity and contextual relevance, a pilot test involving target respondents could have provided additional insights into how senior quality professionals in Malaysian manufacturing companies interpret and respond to the survey items. This methodological trade off was necessitated by access constraints and the need to preserve the target respondent pool and is therefore recognised as a methodological consideration and reflected as a limitation in this study.

3.9 Statistical Analyses

The quantitative data was processed and analysed using statistical software to examine both the demographic information and the statistical models (measurement and structural models) derived from the raw data. Sample characteristics were summarised using descriptive statistics, while inferential statistics were applied to test the proposed hypotheses. Specifically, this study employed Partial Least Squares-Structural Equation Modelling (PLS-SEM) analysis to test the causal relationship between independent variables and dependent variables. Data quality was thoroughly checked to secure the accuracy and reliability of the analysis before proceeding with the PLS-SEM analysis. It involved a detailed data screening and cleaning process, addressing issues such as missing values, outliers, influential responses, straight-liners, speeders and data distribution normality verification (Hair et al., 2014; Moore et al., 2021).

3.10 Descriptive Statistics

Basic features of the data were summarised and represented using descriptive statistics. This includes an overview of the respondents' demographic information and was analysed using SPSS version 31. The data includes gender, position of respondents, duration of service in current position, type of manufacturing business, location, length of business operation and number of employees will be presented in frequencies and percentages.

Descriptive statistics of the questionnaire items were also calculated using the mean values to represent measures of central tendency and the standard deviation to illustrate variability. The mean values provide insight into the overall tendency of respondents' perceptions, indicating which aspects were rated higher or lower on average. Meanwhile, the standard deviation values highlight the degree of variation in responses, demonstrating how consistently participants responded to each item. These metrics provide a fundamental understanding of the data distribution before proceeding with inferential analysis.

3.11 Common Method Variance

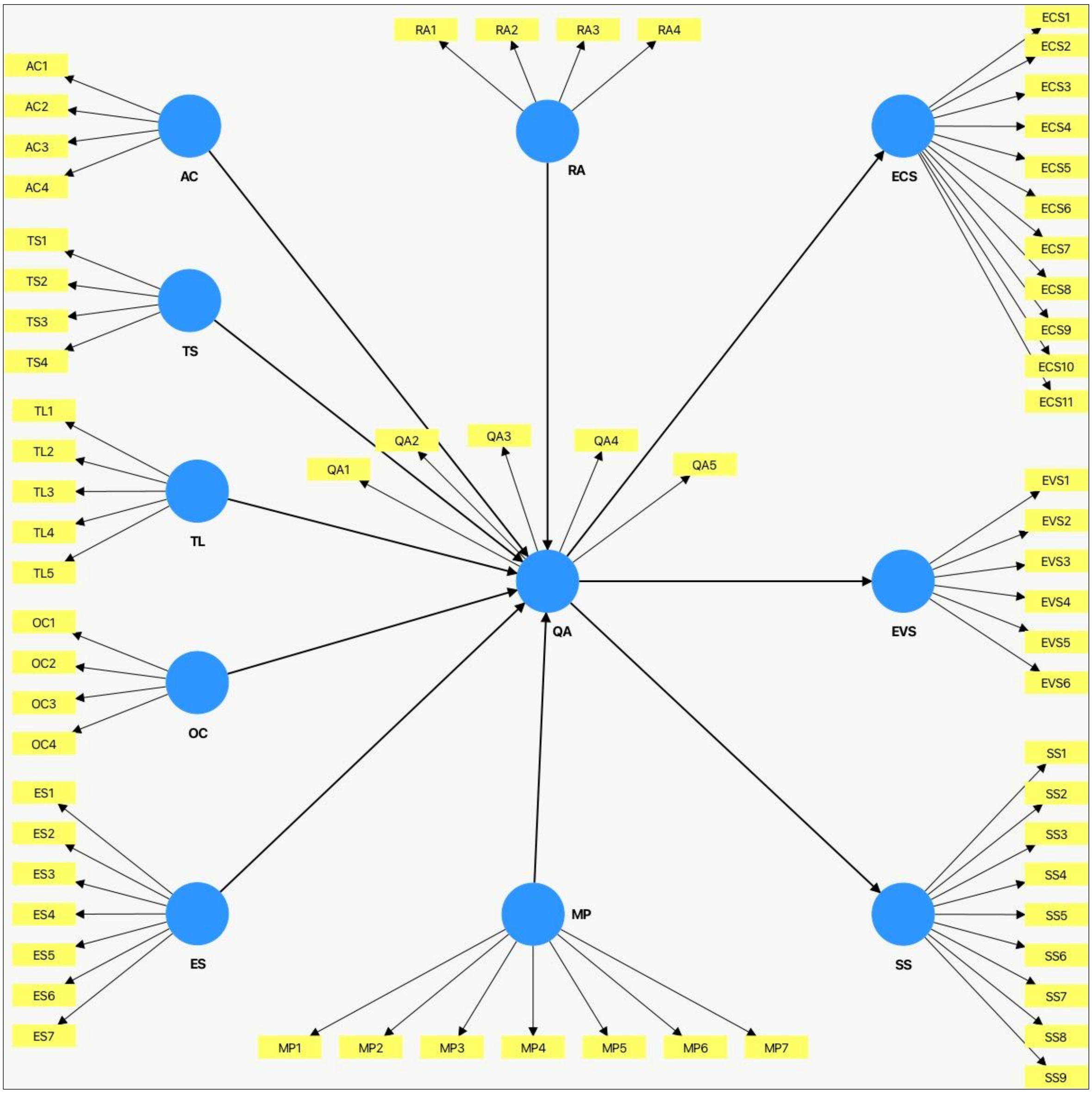
The data were screened using statistical remedies to tackle potential common method variance (CMV). To ensure validity of the findings, Harman's single factor test and the full collinearity variance inflation factor (FVIF) were applied to detect and mitigate any CMV-related issues (Podsakoff et al., 2024).

3.12 Partial Least Square-Structural Equation Modelling (PLS-SEM)

Structural Equation Modelling (SEM) is a robust multivariate technique that enables researchers to model and estimate complex relationships between multiple dependent and independent variables simultaneously (Hair et al., 2022). PLS-SEM has widely adopted across various fields, benefiting from recent advancements that have enhanced its capabilities (Hair et al., 2024). PLS-SEM was chosen in this study for several reasons. First, the research aims to elucidate the relationships between exogenous (independent) and endogenous (dependent) variables. Second, the structural model is inherently complex, incorporating multiple constructs, indicators, and relationships. Moreover, PLS-SEM is advantageous in handling data with both normal and non-normal distribution properties, ensuring robust estimations. Finally, PLS-SEM is recognised for its high statistical power, attributed to its efficient parameter estimation process, making it ideal for this study (Hair et al., 2022).

SmartPLS 4.1.1.2 software was used to validate the PLS-SEM model as demonstrated in Figure 3-3. Two-step approaches, measurement model assessment and structural model assessment were deployed in carrying out the investigation in this study. Firstly, PLS-SEM results were evaluated based on the measurement model. It was then followed by structural model analysis which will be discussed further in following sections.

Figure 3-3:
Research Model



3.12.1 Measurement Model

Confirmatory Factor Analysis (CFA) was used to evaluate the measurement model, in which hypotheses were validated and the factor structure within a measurement model was confirmed. Additionally, it examined whether a set of measured variables can well represent underlying latent constructs (Hair et al., 2014). Indicator reliability, internal consistency reliability, convergent validity, and discriminant validity are the four tests used to assess the reflective measurement model applied in this study.

3.12.1.1 Indicator Reliability

Outer loadings, also referred to as indicator reliability, were selected to evaluate how consistently an indicator or a group of indicators measures the intended construct (Urbach & Ahlemann, 2010). A common guideline for evaluating outer loadings in measurement models suggests that values of 0.708 or higher are generally deemed acceptable. Indicators with outer loadings less than 0.40 are typically advised for exclusion, as they fail to meet the minimum standard. For outer loadings falling between 0.40 and 0.70, their retention should be reconsidered only if removing them enhances the model's internal consistency or convergent validity, bringing these metrics above the recommended thresholds (Hair et al., 2022).

3.12.1.2 Internal Consistency Reliability

Internal consistency reliability assesses how consistently the measured items representing a latent construct align in their measurement, ensuring that they reliably reflect the same underlying concept. Due to limitation of Cronbach's alpha in assessing internal consistency reliability, composite reliability (CR) is considered as a more accurate measure. A major limitation Cronbach's alpha is its assumption that all indicators have even reliability. It is also affected by how many items are included in the scale, which always leads to reliability underestimation. When evaluating CR, values ranging from 0.70 to 0.95 are regarded as acceptable (Hair et al., 2020). A CR score between 0.60 and 0.70 is considered suitable for exploratory research (Hair et al., 2022).

3.12.1.3 Convergent Validity

Convergent validity evaluates the degree to which a measurement tool aligns with other measures assessing the same construct, ensuring that the indicators used for a latent construct are both consistent and reliable. In the context of PLS-SEM, convergent validity is tested using the average variance extracted (AVE). An AVE value of 0.50 and above is deemed sufficient, signifying that, on average, the construct explains over 50% of the variance in its measured indicators (Hair et al., 2022).

3.12.1.4 Discriminant Validity

Discriminant validity measures the degree to which the constructs in a study are truly separate and independent from one another (Ramayah et al., 2018). Cross loading criterion, Fornell and Lacker criterion, and Heterotrait-Monotrait ratio of correlations (HTMT) are three measurement criteria to test discriminant validity. First, each indicator's value should be the highest for its assigned construct compared to other constructs as measured under cross loading criterion (Ramayah et al., 2018). This also means an indicator's outer loading on its assigned construct should be higher than its cross-loadings with other constructs (Hair et al., 2022).

Fornell and Lacker criterion is the second criteria used to indicate discriminant validity. In a model, a construct's square root of AVE should exceed its correlation with any other constructs (Fornell & Larcker, 1981; Hair et al., 2022). Due to efficacy issues detected based on recent studies, HTMT is proposed to test discriminant validity as an alternative approach (Henseler et al., 2015). The stricter HTMT criterion requires a value below 0.85 as evidence of good discriminant validity for constructs that are conceptually distinct. Alternatively, if the HTMT value is below 0.90 for conceptually similar constructs, the discriminant validity is deemed good. In addition, bootstrap confidence intervals help determine if HTMT values fall below a set threshold (e.g. 95% one-sided) for all combinations of constructs, providing a more flexible assessment criterion (Hair et al., 2022; Henseler et al., 2015; Ramayah et al., 2018).

3.12.2 Structural Model

The next phase of the analysis focuses on analysing the structural model. This phase focuses on five key criteria: collinearity, the significance of path coefficients, effect size (f^2), coefficient of determination (R^2) and predictive relevance (Q^2). The main goal of this analysis is to evaluate whether the model can effectively explain and predict the target constructs (Hair et al., 2022).

3.12.2.1 Collinearity Assessment

Detection of any collinearity issues, particularly lateral collinearity will be the first step to be carried out in evaluating the structural model. To address this, the Variance Inflation Factor (VIF) was examined. A VIF value exceeding five, or a more stringent criteria with VIF value of 3.3 or higher, signals potential collinearity problem, which could distort the structural model's estimates. Maintaining VIF within acceptable limits is essential to preserve the accuracy and reliability of the model's results (Hair et al., 2022). In business research, collinearity assessment in PLS-SEM ensures that predictor variables contribute uniquely to explaining outcomes, preventing inflated standard errors and misleading results.

If issue is detected in VIF, researchers can refine their models, enhance result interpretability, and provide more reliable insights for decision-making, especially in industry context.

3.12.2.2 Significance of Path Coefficients

Once collinearity issues are addressed, the next step is to examine the strength of the hypothesised relationships between the constructs using path coefficients, β. These coefficients are standardised within a range of -1 to +1, where values closer to +1 indicating a strong positive relationship and those closer to -1 indicate a strong negative relationship. While path coefficients near ± 1 are often statistically significant, their actual significance will be tested using *p*-values. For a relationship to be considered statistically significant at a common significance level of 5% or 1%, the *p*-value must fall below 0.05 or 0.01, respectively. This ensures that the observed relationships are not due to chance (Hair et al., 2022).

3.12.2.3 Coefficient of Determination (R^2)

The coefficient of determination, denoted as R^2 is used is to measure the explanatory power and predictive accuracy of the model. This range is interpreted between 0 and 1. The higher the value, the greater its predictive accuracy. However, R^2 value is influenced by how many predictors constructs are used in the model and depends on the specific research context. Therefore, when interpreting R^2 in relation to the study's context, it is important to consider benchmarks from similar studies and models with comparable complexity (Hair et al., 2022). Different acceptable rules of thumbs for R^2 have been proposed in PLS-SEM (Ramayah et al., 2018). Chin (1998) suggested that values of 0.67, 0.33, and 0.19 indicate substantial, moderate, and weak predictive accuracy. On the other hand, Hair et al. (2017) recommended more stringent thresholds with R^2 value of 0.25 indicate weak predictive accuracy with limited explanatory power, 0.50 represents moderate accuracy with half the variance explained, and 0.75 signifies strong accuracy with most variance accounted for, ensuring high model reliability. Given that Quality 4.0 adoption is an emerging and at early stage of adoption research in Malaysian manufacturing sector, this study adopts guidelines from Chin (1998) as they provide a more appropriate reference point for models in nascent research areas. However, guidelines from Hair et al. (2017) are acknowledged as the more rigorous alternative for mature theoretical contexts.

3.12.2.4 Effect Size (f^2)

The impact of an exogenous construct on the explanation of an endogenous construct, specifically in terms of R^2 is examined using the effect size, f^2 (Ramayah et al., 2018). The f^2 values indicate effect size, where 0.02 represents a small effect with minimal impact, 0.15 signifies a medium effect with moderate influence, and 0.35 denotes a large effect with substantial impact on the endogenous variable (Cohen, 1988; Ramayah et al., 2018). In business research, effect size, f^2 in PLS-SEM helps assess the strength of relationships between predictor and outcome variables, complementing statistical significance.

3.12.2.5 Predictive Relevance (Q^2)

Stone-Geisser's Q^2, derived through the blindfolding procedure, is commonly used metric to evaluate the predictive relevance of the path model, ensuring its ability to generate meaningful predictions (Ramayah et al., 2018). If Q^2 exceeds 0, it shows that the exogenous constructs provide sufficient predictive relevance for the examined endogenous construct (Hair et al., 2017).

3.13 Chapter Summary

Chapter 3 outlies the research methodology, detailing the approach taken to secure the validity and reliability of the findings. It starts with an introduction to the research design, specifying the adoption of a quantitative, cross-sectional survey method to examine the relationship between Quality 4.0 adoption and corporate sustainability performance among Malaysian manufacturing companies. The study follows a deductive approach, utilising a structured questionnaire for data collection. The target population consists of manufacturing companies registered under the Federation of Malaysian Manufacturers (FMM), with a sampling frame filtered based on company size. Systematic random sampling method is employed to ensure a representative sample, with the minimum final sample size determined using G*Power software.

Data collection is conducted through an online survey distributed via email, accompanied by a cover letter explaining the study's purpose. Efforts to enhance response rates include email and messaging follow-ups. The questionnaire is structured in six sections, covering demographic information, technological, organisational, and environmental contexts, Quality 4.0 adoption, and corporate sustainability performance. Measurement items are adapted from established research, with responses captured on Likert scales.

To ensure data reliability, the study applies statistical validation techniques, such as face and content validity through expert review pre-testing. Data analysis is performed using SmartPLS 4.1.1.2, with Partial Least Squares-Structural Equation Modelling (PLS-SEM) used to test research hypotheses. The study also incorporates multiple statistical tests, including common method variance checks, descriptive statistics using SPSS, measurement model and structural model assessments.

In summary, this chapter portrays the methodological framework, ensuring robust findings on the connection between Quality 4.0 adoption and corporate sustainability performance through rigorous data collection, validation and analysis.

CHAPTER 4:

FINDINGS AND DISCUSSIONS

4.1 Introduction

Chapter 4 begins with a preliminary data analysis which involves screening for missing data, detecting suspicious response patterns such as straight lining, and assessing the normality of data distribution through skewness and kurtosis. It is followed by common method variance (CMV) examination to mitigate the potential impact of measurement bias and outlining respondents' profile. Subsequent sections summarise the assessment of the measurement model in terms of reliability and validity, followed by an evaluation of the structural model through key statistical indicators and hypotheses testing. The chapter ends with a summary of the main findings, setting the foundation for final chapter of this study.

4.2 Preliminary Data Analysis

In total, 127 valid responses were obtained for this study. Although the sample size achieved exceeded the minimum requirement for statistical analysis, the relatively low response rate is recognised as a characteristic of organisational-level survey research involving senior respondents. The implications of potential non-response bias have been explicitly discussed as a methodological consideration in Chapter 3 and are reflected as a study limitation in Chapter 5.

The first stage of preliminary data analysis was conducted using SPSS version 31 to examine any missing data from the dataset. As expected, no missing data was detected since the Google Forms survey was designed with mandatory response settings.

After addressing missing values, the dataset was further evaluated for suspicious response patterns. Two cases of straight lining were identified, where respondents provided identical responses across all items for 7-point Likert scale and 5-point Likert scale respectively. Hence, these cases were considered invalid and were removed from the dataset to ensure the quality and reliability of the analysis. As a result, the number of valid responses reduced from 127 to 125.

The analysis was further continued to test the normality of the data distribution. As recommended by Hair et al. (2022), skewness and kurtosis values were used to examine the normality with acceptable thresholds within ±2. All variables met these criteria, as summarised in Table 4-1 and indicating that the data did not demonstrate severe deviations from normal distribution.

Finally, common method variance (CMV) was examined to address the potential issue of measurement bias. Harman's single factor test was conducted in SPSS version 31 using principal component analysis. The result as demonstrated in Table 4-2 showed that the first component accounted for 29.428% of the total variance, which is well below the 50% cut-off value recommended by Podsakoff et al. (2024).

In addition, a full collinearity assessment was conducted by assessing the variance inflation factor (VIF) for both the outer and inner model using SmartPLS 4.1.1.2 software. The outcome of the analysis summarised that the VIF values ranged from 1.16 to 2.969 for the outer model and from 1.00 to 2.059 for the inner model. All values as summarised in Table 4-9 were below the suggested threshold value of 3.3 for the common method bias test (Podsakoff et al., 2024). These results indicate that CMV did not pose a major concern to the validity of the findings in this study. Nevertheless, given the use of a single key informat to report on organisational level constructs, the CMV assessment is interpreted in conjunction with the procedural remedies outlined in Chapter 3 and the broader limitations discussed in Chapter 5.

Table 4-1:
Skewness and Kurtosis

Construct	Item	Skewness	Kurtosis
Relative Advantage (RA)	RA1	-0.669	-0.042
	RA2	-0.513	-0.387
	RA3	-0.336	-0.471
	RA4	-0.696	-0.366
AI Compatibility (AC)	AC1	-0.411	-0.467
	AC2	-0.596	-0.214
	AC3	-0.481	-0.211
	AC4	-0.536	-0.314
Top Management Support (TS)	TS1	-0.441	-0.468
	TS2	-0.353	-0.491
	TS3	-0.513	-0.522
	TS4	-0.350	-0.713
Transformational Leadership (TL)	TL1	-1.148	1.177
	TL2	-0.719	1.096
	TL3	-0.481	0.101
	TL4	-0.871	0.921
	TL5	-0.435	-0.385
Organisational Culture (OC)	OC1	-0.394	-0.241
	OC2	-0.358	-0.626
	OC3	-0.515	-0.355
	OC4	-0.423	-0.448
External Support (ES)	ES1	-0.465	-0.318
	ES2	-0.311	-0.571
	ES3	-0.388	-0.175
	ES4	-0.312	-0.321
	ES5	-0.359	-0.229
	ES6	-0.361	-0.336
	ES7	-0.077	-0.504
Market Pressure (MP)	MP1	-0.392	-0.240
	MP2	-0.354	-0.141
	MP3	-0.249	-0.209
	MP4	-0.247	-0.418
	MP5	-0.011	-0.418
	MP6	-0.337	-0.323
	MP7	-0.575	-0.260
Quality 4.0 Adoption (QA)	QA1	-0.455	-0.597
	QA2	-0.453	-0.591
	QA3	-0.415	-0.724
	QA4	-0.340	-0.691
	QA5	-0.387	-0.471
Economic Sustainability (ECS)	ECS1	-0.121	-0.801
	ECS2	-0.162	-0.883
	ECS3	-0.097	-0.762
	ECS4	-0.307	-0.981
	ECS5	0.028	-0.910
	ECS6	-0.389	-0.897
	ECS7	-0.214	-0.924

Construct	Item	Skewness	Kurtosis
	ECS8	-0.150	-0.838
	ECS9	-0.332	-0.810
	ECS10	-0.168	-0.857
	ECS11	-0.159	-0.933
Environmental Sustainability (EVS)	EVS1	-0.248	-0.804
	EVS2	-0.248	-0.804
	EVS3	-0.194	-0.683
	EVS4	0.239	-0.674
	EVS5	0.040	-0.778
	EVS6	0.060	-0.714
Social Sustainability (SS)	SS1	-0.327	-0.786
	SS2	-0.189	-0.691
	SS3	-0.368	-0.562
	SS4	-0.004	-0.648
	SS5	-0.088	-0.817
	SS6	-0.279	-0.685
	SS7	-0.036	-0.779
	SS8	-0.327	-0.763
	SS9	-0.355	-0.712

Table 4-2:
Total Variance Explained

	Initial Eigenvalues			**Extraction Sums of Squared Loadings**		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	19.423	29.428	**29.428**	19.423	29.428	**29.428**
2	5.299	8.029	37.458	5.299	8.029	37.458
3	3.896	5.903	43.361	3.896	5.903	43.361
4	2.899	4.392	47.753	2.899	4.392	47.753
5	2.579	3.908	51.662	2.579	3.908	51.662
6	2.258	3.421	55.083	2.258	3.421	55.083
7	2.066	3.130	58.213	2.066	3.130	58.213
8	1.652	2.503	60.716	1.652	2.503	60.716
9	1.565	2.372	63.087	1.565	2.372	63.087
10	1.352	2.048	65.135	1.352	2.048	65.135
11	1.257	1.904	67.039	1.257	1.904	67.039
12	1.139	1.726	68.765	1.139	1.726	68.765
13	1.098	1.664	70.429	1.098	1.664	70.429
14	1.058	1.603	72.031	1.058	1.603	72.031
15	0.966	1.463	73.495			
16	0.927	1.405	74.899			
17	0.883	1.339	76.238			
18	0.841	1.274	77.512			
19	0.804	1.218	78.730			
20	0.772	1.170	79.900			
21	0.752	1.139	81.040			

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
22	0.683	1.035	82.075			
23	0.636	0.963	83.038			
24	0.596	0.903	83.941			
25	0.572	0.866	84.807			
26	0.568	0.861	85.667			
27	0.542	0.822	86.489			
28	0.531	0.804	87.294			
29	0.486	0.737	88.031			
30	0.468	0.709	88.740			
31	0.434	0.657	89.397			
32	0.423	0.640	90.037			
33	0.416	0.631	90.668			
34	0.388	0.588	91.256			
35	0.380	0.575	91.831			
36	0.358	0.542	92.373			
37	0.353	0.535	92.908			
38	0.320	0.485	93.393			
39	0.316	0.479	93.872			
40	0.311	0.471	94.342			
41	0.289	0.437	94.780			
42	0.282	0.427	95.207			
43	0.267	0.404	95.611			
44	0.239	0.362	95.973			
45	0.222	0.337	96.310			
46	0.215	0.326	96.635			
47	0.204	0.308	96.944			
48	0.183	0.278	97.222			
49	0.170	0.258	97.479			
50	0.168	0.255	97.734			
51	0.162	0.245	97.979			
52	0.147	0.223	98.202			
53	0.137	0.208	98.410			
54	0.131	0.199	98.609			
55	0.115	0.175	98.784			
56	0.108	0.163	98.947			
57	0.097	0.148	99.094			
58	0.091	0.138	99.232			
59	0.084	0.127	99.359			
60	0.081	0.122	99.481			
61	0.073	0.111	99.592			
62	0.069	0.105	99.697			
63	0.061	0.093	99.789			
64	0.055	0.083	99.872			
65	0.053	0.080	99.953			
66	0.031	0.047	100.000			

Note: Extraction Method = Principal Component Analysis

4.3 Respondents' Profile

The demographic characteristics of the respondents are summarised in Table 4-3 based on a total of 125 valid responses. Firstly, 56.0% of the respondents were male, and the female respondents accounted for 44% of the gender distribution. Among the respondents, 35.2% hold a position of Senior Quality Executives, followed by Quality Managers at 34.4%, with smaller distribution representing Senior Quality Managers at 8.8%, Quality Directors at 8.0%, and others including Chairman, Head of Technology and Innovation, Operations Manager, Production Manager, Senior Technical Lead etc. at 13.6%. These responses were retained in the analysis because quality management and the adoption of Quality 4.0 are inherently cross-functional initiatives that require the active commitment of decision makers across different functions of the manufacturing businesses. Their inclusion reflects actual business scenarios where quality transformation extends beyond the quality department and involves broader organisational leadership team.

Regarding service duration, 51.2% of the respondents had more than 10 years of working experience in the company, while 24.0% had between 5 to 10 years, 17.6% had 2 to 5 years, and 7.2% reported with less than 2 years of service. In terms of business types, 50.4% of the respondents came from electrical and electronics industry, followed by fabricated metals at 8.8%, plastics at 4.8% and several other industries, each contributing smaller proportions of this demographic characteristic.

Most companies had been in operation for more than 20 years (87.2%), with only a small percentage operating between 10 to 20 years (6.4%), or less than 10 years (6.4%). In a similar manner, majority of respondents worked in large manufacturing companies with more than 200 employees (87.2), while 12.8% were from medium manufacturing companies with 75 to 200 employees.

Geographically, respondents were spread across several states, with the largest percentage coming from Selangor (35.2%), followed by Penang (28.0%), Sarawak (16.8%), Johor (10.4%), and other states with smaller proportions.

Table 4-3:
Demographic Characteristics of Respondents

Demographic Profile	Respondents (N=125)	Percentage (%)
Gender		
Male	70	56.0
Female	55	44.0
Position		
Senior Quality Executive	44	35.2
Quality Manager	43	34.4
Senior Quality Manager	11	8.8
Quality Director	10	8.0
Others	17	13.6
Service Duration		
1 to < 2 years	9	7.2
2 to < 5 years	22	17.6
5 to < 10 years	30	24.0
≥ 10 years	64	51.2
Types of Business		
Basic Metal	3	2.4
Chemical (including Petroleum)	6	4.8
Electrical & Electronics	63	50.4
Fabricated Metals	11	8.8
Food, Beverage, and Tobacco	3	2.4
Machinery & Equipment	5	4.0
Medical, Precision & Optical Instruments	6	4.8
Pharmaceutical	2	1.6
Plastics	4	3.2
Rubber	6	4.8
Transport, Vehicle & Equipment	4	3.2
Others	15	12
Location		
Johor	13	10.4
Kuala Lumpur	3	2.4
Melaka	3	2.4
Penang	35	28.0
Perak	4	3.2
Sabah	2	1.6
Sarawak	21	16.8
Selangor	44	35.2

4.4 The Statistical Overview of the Variables

Descriptive statistics of the questionnaire items including mean and standard deviation were computed. The items were measured using 7-point and 5-point Likert scales in this study. RA, AC, TS, TL, OC, ES, MP and QA were measured using a 7-Point Likert Scales, while ECS, EVS, and SS were measured using a 5-point Likert Scale.

Overall mean values for the constructs measured on a 7-point Likert scale ranged from moderate to high (4.25 to 6.03). Transformational Leadership (TL1-TL5) recorded the highest means, ranging from 4.94 to 6.03, followed by Relative Advantage (RA1-RA4) with mean values between 5.20 to 5.46. Top Management Support (TS1-TS4) showed means values between 5.11 to 5.32, while AI Compatibility (AC1-AC4) and Organisational Culture (OC1-OC4) recorded means in the range of 5.05 to 5.22 and 4.98 to 5.17 respectively. More moderate results were observed for External Support (ES1-ES7), with means of 4.53 to 4.89, and Market Pressure (MP1-MP7), ranging from 4.25 to 5.22. For the dependent construct, Quality 4.0 Adoption (QA1-QA5) showed means between 4.96 to 5.22.

For constructs measured on a 5-point Likert scale, Economic Sustainability (ECS1-ECS11) recorded the highest means, ranging from 3.62 to 3.90, followed by Social Sustainability (SS1-SS9) with mean values between 3.38 to 3.86. Lastly, Environmental Sustainability (EVS1-EVS6) showed the lowest average means, ranging from 3.48 to 3.78.

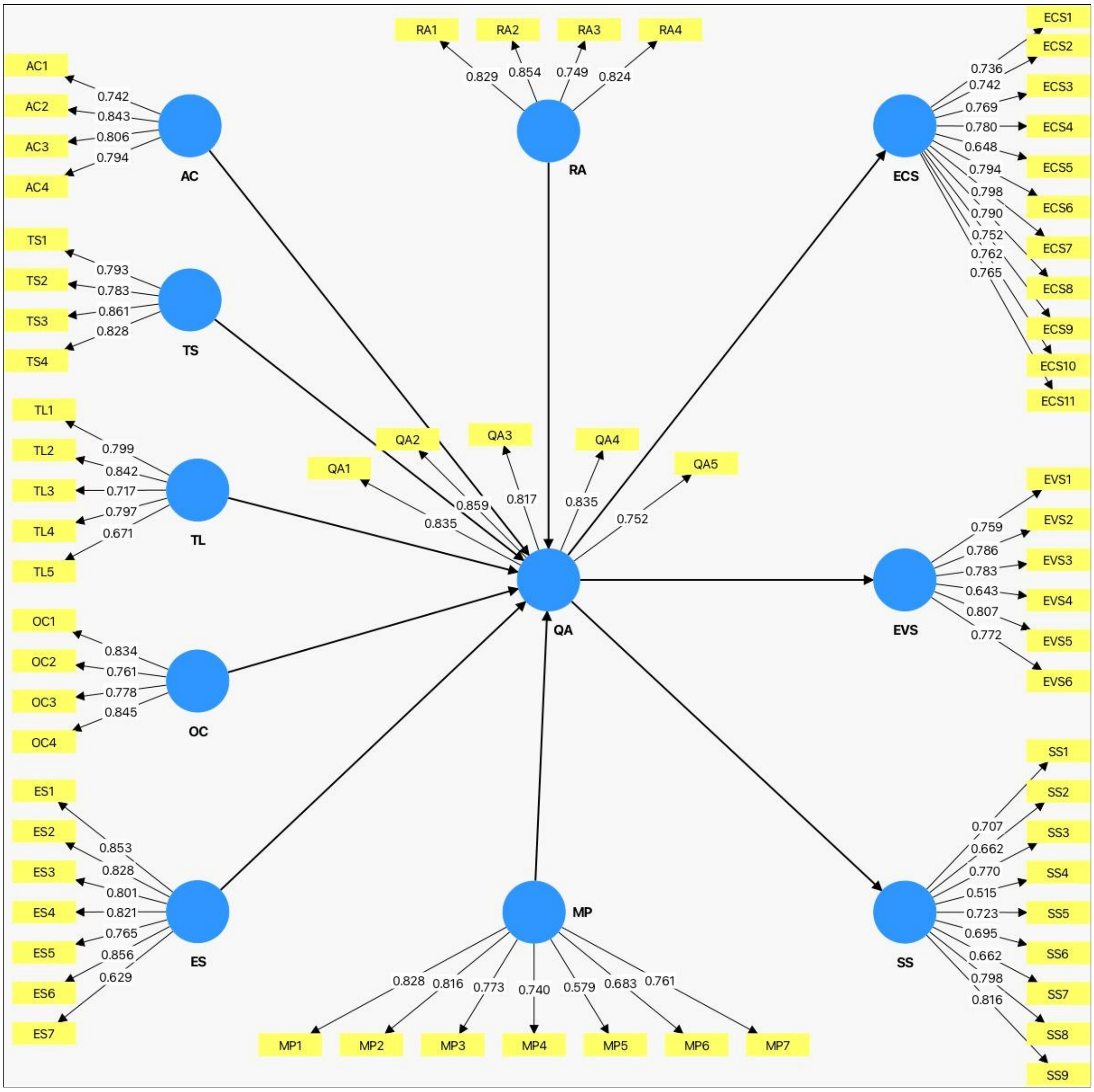
In terms of standard deviations (SD), variance observed in responses was rather moderate across all constructs. For the 7-point Likert scale items, Transformational Leadership (TL1-TL5) has SD between 0.838 to 1.297, while Top Management Support (TS1-TS4) ranged from 1.189 to 1.318. Organisational Culture (OC1-OC4) recorded SD of 1.263 to 1.302, while AI Compatibility (AC1-AC4) ranged from 1.275 to 1.330. Relative Advantage (RA1-RA4) showed slightly higher SD of 1.259 to 1.389. External Support (ES1-ES7) and Market Pressure (MP1-MP7) were more varied, ranging between 1.346 to 1.433 and 1.375 to 1.501 respectively. For the dependent construct, Quality 4.0 Adoption (QA1-QA4) recorded SD of 1.315 to 1.39.

For the 5-Point Likert scale constructs, standard deviations for Environmental Sustainability (EVS1-EVS6) recorded ranging from 0.871 to 0.921, followed by Social Sustainability (SS1-SS9) ranging from 0.887 to 0.989 and finally, Economic Sustainability (ECS1-ECS11) SD ranged from 0.898 to 0.966.

4.5 Assessment of the Measurement Model

In this session, measurement model was assessed using Confirmatory Factor Analysis (CFA) to evaluate the reliability and validity of the construct measures by conducting indicator reliability, internal consistency reliability, convergent validity, and discriminant validity tests. Figure 4-1 illustrates the measurement model generated using SmartPLS 4.1.1.2 with an overview of outer loadings for each measurement item.

Figure 4-1:
Measurement Model



4.5.1 Indicator Reliability

Table 4-4 summarises the indicator reliability based on outer loadings values. It is suggested that indicators with outer loadings of 0.708 or higher are considered acceptable, those below 0.40 should be removed, and those between 0.40 and 0.70 can be retained when the construct meets the minimum AVE result of 0.50 or when other strong indicators keep AVE and CR at acceptable levels (Hair et al., 2022; Ramayah et al., 2018). Based on the results, most indicators loaded above 0.708 demonstrated a good indicator reliability of the indicators, while smaller sets fell within the 0.50 to 0.70 range. Borderline indicators include TL5, MP5, MP6, ECS5, EVS4, SS2, SS4, SS6, and SS7 with values of 0.671, 0.579, 0.683, 0.648, 0.643, 0.662, 0.515, 0.695, and 0.662 respectively. These lower outer loadings items were retained because each construct met the minimum requirement of AVE result of 0.50 and with CR > 0.70. Based on the results, all items used to represent the constructs have satisfactory indicator reliability.

4.5.2 Internal Consistency Reliability

Internal consistency reliability was assessed using composite reliability (CR) due to Cronbach's alpha having certain limitations in evaluating internal consistency reliability. Hence, CR is often considered a more accurate measure and values between 0.70 and 0.95 are generally regarded as acceptable (Hair et al., 2020). Based on the results shown in Table 4-4, all the constructs have demonstrated satisfactory internal consistency reliability with CR values ranging from 0.874 to 0.937.

4.5.3 Convergent Validity

Convergent validity was examined using average variance extracted (AVE). As tabulated in Table 4-4, all constructs met the minimum threshold of 0.50, as recommended by Hair et al. (2022), with AVE values ranging from 0.505 to 0.673. The measurement model has demonstrated adequate convergent validity.

Table 4-4:
Summary of Construct Reliability and Validity

Construct	Item	Outer Loadings	Cronbach's Alpha	CR (ρ_c)	AVE
Relative Advantage (RA)	RA1	0.829	0.831	0.887	0.664
	RA2	0.854			
	RA3	0.749			
	RA4	0.824			
AI Compatibility (AC)	AC1	0.742	0.809	0.874	0.635
	AC2	0.843			
	AC3	0.806			
	AC4	0.794			
Top Management Support (TS)	TS1	0.793	0.834	0.889	0.667
	TS2	0.783			
	TS3	0.861			
	TS4	0.828			
Transformational Leadership (TL)	TL1	0.799	0.831	0.877	0.589
	TL2	0.842			
	TL3	0.717			
	TL4	0.797			
	TL5	0.671			
Organisational Culture (OC)	OC1	0.834	0.819	0.880	0.649
	OC2	0.761			
	OC3	0.778			
	OC4	0.845			
External Support (ES)	ES1	0.853	0.906	0.923	0.634
	ES2	0.828			
	ES3	0.801			
	ES4	0.821			
	ES5	0.765			
	ES6	0.856			
	ES7	0.629			
Market Pressure (MP)	MP1	0.828	0.882	0.896	0.554
	MP2	0.816			
	MP3	0.773			
	MP4	0.740			
	MP5	0.579			
	MP6	0.683			
	MP7	0.761			
Quality 4.0 Adoption (QA)	QA1	0.835	0.878	0.911	0.673
	QA2	0.859			
	QA3	0.817			
	QA4	0.835			
	QA5	0.752			
Economic Sustainability (ECS)	ECS1	0.736	0.926	0.937	0.576
	ECS2	0.742			
	ECS3	0.769			
	ECS4	0.780			
	ECS5	0.648			
	ECS6	0.794			

Construct	Item	Outer Loadings	Cronbach's Alpha	CR (ρ_c)	AVE
	ECS7	0.798			
	ECS8	0.790			
	ECS9	0.752			
	ECS10	0.762			
	ECS11	0.765			
Environmental Sustainability (EVS)	EVS1	0.759	0.854	0.891	0.578
	EVS2	0.786			
	EVS3	0.783			
	EVS4	0.643			
	EVS5	0.807			
	EVS6	0.772			
Social Sustainability (SS)	SS1	0.707	0.878	0.900	0.505
	SS2	0.662			
	SS3	0.770			
	SS4	0.515			
	SS5	0.723			
	SS6	0.695			
	SS7	0.662			
	SS8	0.798			
	SS9	0.816			

4.5.4 Discriminant Validity

Discriminant validity of this study was assessed through three approaches, namely the cross loading criterion, the Fornell and Lacker criterion, and the Heterotrait-Monotrait (HTMT) ratio of correlations. The results of these assessments are presented in Table 4-5, Table 4-6, and Table 4-7 respectively. The subsequent sections analyse each criterion in detail and provide explanation of the discriminant validity evaluation outcome.

4.5.4.1 Cross Loading Criterion

Table 4-5 presents the cross loading of all measurement items. Each indicator demonstrated its highest loading on its intended construct, with substantially lower loading on other constructs, meeting the guidelines suggested by Hair et al. (2022). These results supported the discriminant validity of the measurement model as first assessment.

Table 4-5:
Cross Loading Matrix

	RA	AC	TS	TL	OC	ES	MP	QA	ECS	EVS	SS
RA1	**0.829**	0.487	0.408	0.134	0.414	0.241	0.179	0.467	0.329	0.351	0.479
RA2	**0.854**	0.484	0.377	0.107	0.395	0.310	0.170	0.450	0.395	0.393	0.381
RA3	**0.749**	0.533	0.333	0.250	0.331	0.346	0.274	0.426	0.443	0.327	0.297
RA4	**0.824**	0.479	0.398	0.078	0.374	0.233	0.207	0.537	0.437	0.332	0.379
AC1	0.459	**0.742**	0.309	0.146	0.383	0.166	0.238	0.320	0.234	0.163	0.209
AC2	0.543	**0.843**	0.401	0.314	0.465	0.223	0.341	0.457	0.413	0.319	0.323
AC3	0.432	**0.806**	0.484	0.340	0.447	0.329	0.306	0.377	0.312	0.186	0.278
AC4	0.491	**0.794**	0.397	0.239	0.406	0.188	0.368	0.389	0.414	0.214	0.185
TS1	0.413	0.488	**0.793**	0.521	0.445	0.328	0.336	0.527	0.372	0.371	0.450
TS2	0.257	0.353	**0.783**	0.484	0.373	0.437	0.325	0.412	0.346	0.363	0.347
TS3	0.441	0.392	**0.861**	0.427	0.378	0.376	0.233	0.527	0.377	0.414	0.439
TS4	0.390	0.392	**0.828**	0.470	0.408	0.340	0.274	0.466	0.280	0.380	0.432
TL1	0.010	0.122	0.305	**0.799**	0.214	0.362	0.361	0.217	0.180	0.283	0.186
TL2	0.151	0.286	0.458	**0.842**	0.365	0.389	0.405	0.327	0.239	0.265	0.222
TL3	-0.071	0.144	0.214	**0.717**	0.216	0.341	0.262	0.192	0.088	0.190	0.060
TL4	0.109	0.208	0.410	**0.797**	0.301	0.379	0.387	0.297	0.221	0.268	0.234
TL5	0.277	0.378	0.626	**0.671**	0.315	0.362	0.223	0.421	0.194	0.279	0.316
OC1	0.377	0.468	0.378	0.356	**0.834**	0.295	0.176	0.512	0.358	0.375	0.328
OC2	0.383	0.376	0.421	0.321	**0.761**	0.318	0.186	0.459	0.295	0.306	0.367
OC3	0.383	0.370	0.431	0.284	**0.778**	0.323	0.219	0.478	0.420	0.376	0.418
OC4	0.358	0.503	0.362	0.290	**0.845**	0.282	0.295	0.509	0.362	0.375	0.257
ES1	0.326	0.290	0.449	0.379	0.407	**0.853**	0.316	0.477	0.296	0.296	0.273
ES2	0.264	0.231	0.434	0.387	0.382	**0.828**	0.263	0.362	0.305	0.311	0.276
ES3	0.311	0.233	0.345	0.467	0.226	**0.801**	0.392	0.343	0.350	0.446	0.294
ES4	0.262	0.200	0.272	0.375	0.250	**0.821**	0.438	0.263	0.213	0.313	0.237
ES5	0.276	0.208	0.250	0.358	0.311	**0.765**	0.285	0.280	0.235	0.294	0.150
ES6	0.229	0.206	0.396	0.425	0.219	**0.856**	0.386	0.298	0.282	0.313	0.301
ES7	0.191	0.186	0.270	0.333	0.233	**0.629**	0.294	0.087	0.119	0.116	0.160
MP1	0.175	0.370	0.297	0.352	0.257	0.345	**0.828**	0.357	0.333	0.223	0.350
MP2	0.148	0.305	0.244	0.340	0.189	0.413	**0.816**	0.286	0.273	0.385	0.327
MP3	0.127	0.202	0.180	0.376	0.151	0.356	**0.773**	0.269	0.298	0.268	0.256
MP4	0.146	0.271	0.193	0.315	0.137	0.338	**0.740**	0.236	0.287	0.276	0.262
MP5	-0.029	0.142	-0.006	0.321	0.033	0.192	**0.579**	0.053	0.083	0.148	0.057
MP6	0.008	0.064	0.082	0.296	-0.045	0.304	**0.683**	0.096	0.234	0.295	0.172
MP7	0.356	0.400	0.431	0.293	0.323	0.243	**0.761**	0.502	0.449	0.439	0.400
QA1	0.507	0.362	0.490	0.323	0.508	0.253	0.318	**0.835**	0.548	0.587	0.455
QA2	0.459	0.370	0.515	0.300	0.442	0.357	0.362	**0.859**	0.601	0.497	0.526
QA3	0.555	0.531	0.468	0.334	0.523	0.338	0.364	**0.817**	0.557	0.452	0.493
QA4	0.509	0.363	0.568	0.366	0.531	0.370	0.321	**0.835**	0.578	0.445	0.529
QA5	0.341	0.385	0.396	0.377	0.495	0.408	0.422	**0.752**	0.484	0.490	0.412
ECS1	0.324	0.343	0.240	0.207	0.282	0.206	0.243	0.438	**0.736**	0.327	0.371
ECS2	0.314	0.227	0.272	0.206	0.241	0.269	0.355	0.470	**0.742**	0.516	0.384
ECS3	0.382	0.289	0.232	0.231	0.349	0.308	0.402	0.503	**0.769**	0.481	0.405
ECS4	0.468	0.452	0.413	0.207	0.422	0.327	0.290	0.570	**0.780**	0.459	0.407
ECS5	0.230	0.226	0.264	0.281	0.234	0.272	0.407	0.392	**0.648**	0.352	0.458
ECS6	0.371	0.381	0.262	0.145	0.383	0.208	0.277	0.537	**0.794**	0.360	0.427
ECS7	0.415	0.418	0.377	0.163	0.412	0.206	0.342	0.573	**0.798**	0.486	0.498

	RA	AC	TS	TL	OC	ES	MP	QA	ECS	EVS	SS
ECS8	0.354	0.300	0.389	0.212	0.326	0.261	0.400	0.568	**0.790**	0.508	0.444
ECS9	0.410	0.360	0.353	0.161	0.366	0.282	0.277	0.508	**0.752**	0.474	0.447
ECS10	0.387	0.223	0.342	0.156	0.272	0.287	0.249	0.515	**0.762**	0.461	0.469
ECS11	0.412	0.403	0.345	0.192	0.389	0.234	0.363	0.528	**0.765**	0.480	0.425
EVS1	0.396	0.277	0.415	0.337	0.335	0.350	0.329	0.522	0.568	**0.759**	0.504
EVS2	0.369	0.145	0.358	0.239	0.314	0.288	0.324	0.472	0.458	**0.786**	0.440
EVS3	0.356	0.235	0.343	0.215	0.357	0.275	0.326	0.533	0.449	**0.783**	0.492
EVS4	0.199	0.153	0.243	0.268	0.232	0.273	0.321	0.349	0.337	**0.643**	0.356
EVS5	0.288	0.267	0.445	0.275	0.463	0.326	0.369	0.467	0.445	**0.807**	0.438
EVS6	0.306	0.196	0.287	0.238	0.297	0.265	0.225	0.334	0.387	**0.772**	0.352
SS1	0.323	0.223	0.362	0.085	0.230	0.110	0.246	0.394	0.334	0.348	**0.707**
SS2	0.281	0.177	0.187	0.077	0.207	0.232	0.279	0.351	0.469	0.453	**0.662**
SS3	0.383	0.261	0.484	0.254	0.364	0.285	0.250	0.492	0.433	0.453	**0.770**
SS4	0.026	0.013	0.124	0.183	0.064	0.143	0.181	0.164	0.212	0.196	**0.515**
SS5	0.381	0.249	0.396	0.348	0.276	0.276	0.331	0.383	0.352	0.389	**0.723**
SS6	0.222	0.216	0.382	0.353	0.351	0.267	0.326	0.402	0.390	0.403	**0.695**
SS7	0.222	0.021	0.204	0.169	0.127	0.082	0.156	0.316	0.334	0.296	**0.662**
SS8	0.439	0.314	0.416	0.191	0.402	0.221	0.356	0.493	0.523	0.502	**0.798**
SS9	0.504	0.347	0.516	0.228	0.454	0.310	0.408	0.585	0.479	0.518	**0.816**

4.5.4.2 Fornell and Lacker Criterion

Table 4-6 presents the second assessment of discriminant validity using the Fornell and Lacker criterion. The square roots of the AVE displayed on the diagonal exceeded the corresponding inter-construct correlation in every case. Based on the summary, the Fornell and Lacker criterion was fulfilled for all constructs, meeting the guidelines suggested by Fornell and Larcker (1981) and Hair et al. (2022). These results further supported the discriminant validity of the measurement model.

Table 4-6:
Fornell and Lacker Matrix

	RA	AC	TS	TL	OC	ES	MP	QA	ECS	EVS	SS
RA	**0.815**										
AC	0.606	**0.797**									
TS	0.467	0.501	**0.817**								
TL	0.169	0.333	0.581	**0.768**							
OC	0.465	0.536	0.492	0.389	**0.805**						
ES	0.342	0.285	0.449	0.485	0.377	**0.796**					
MP	0.433	0.397	0.355	0.425	0.272	0.416	**0.744**				
QA	0.581	0.490	0.597	0.413	0.608	0.418	0.433	**0.820**			
ECS	0.493	0.439	0.423	0.255	0.446	0.342	0.430	0.676	**0.759**		
EVS	0.429	0.284	0.468	0.345	0.445	0.392	0.420	0.602	0.591	**0.760**	
SS	0.473	0.317	0.515	0.296	0.423	0.313	0.410	0.590	0.567	0.577	**0.711**

4.5.4.3 Heterotrait-Monotrait Ratio of Correlations (HTMT)

Discriminant validity was further evaluated using the Heterotrait-Monotrait (HTMT) ratios of correlations as third assessment approach. All HTMT values were below the stringent HTMT .85 criterion and thus also below the conservative criterion of HTMT .90 rule (Hair et al., 2022; Henseler et al., 2015) as displayed in Table 4-7. In addition, 95% one-sided bootstrap confidence intervals of HTMT were also presented in Table 4-8. The upper bound of the CIs remained below the set threshold of 0.85 and 0.90, provided additional evidence that the discriminant validity of the measurement model is satisfied.

Table 4-7:
HTMT Matrix

	RA	AC	TS	TL	OC	ES	MP	QA	ECS	EVS	SS
RA											
AC	0.739										
TS	0.550	0.603									
TL	0.245	0.361	0.628								
OC	0.565	0.653	0.597	0.443							
ES	0.389	0.323	0.501	0.551	0.423						
MP	0.242	0.386	0.330	0.513	0.270	0.470					
QA	0.673	0.576	0.689	0.444	0.719	0.427	0.392				
ECS	0.556	0.492	0.474	0.278	0.506	0.354	0.416	0.744			
EVS	0.500	0.325	0.543	0.395	0.523	0.423	0.436	0.679	0.649		
SS	0.510	0.352	0.558	0.331	0.460	0.334	0.393	0.637	0.614	0.631	

Table 4-8:
HTMT Bootstrap Confidence Interval

Construct Pair	5%	95.0%
ECS <-> AC	0.361	0.617
ES <-> AC	0.181	0.461
ES <-> ECS	0.234	0.471
EVS <-> AC	0.205	0.430
EVS <-> ECS	0.530	0.748
EVS <-> ES	0.278	0.556
MP <-> AC	0.261	0.503
MP <-> ECS	0.296	0.523
MP <-> ES	0.312	0.604
MP <-> EVS	0.299	0.561
OC <-> AC	0.507	0.775
OC <-> ECS	0.356	0.640
OC <-> ES	0.282	0.554
OC <-> EVS	0.386	0.641
OC <-> MP	0.170	0.354
QA <-> AC	0.428	0.697
QA <-> ECS	0.646	0.827
QA <-> ES	0.299	0.544
QA <-> EVS	0.563	0.782

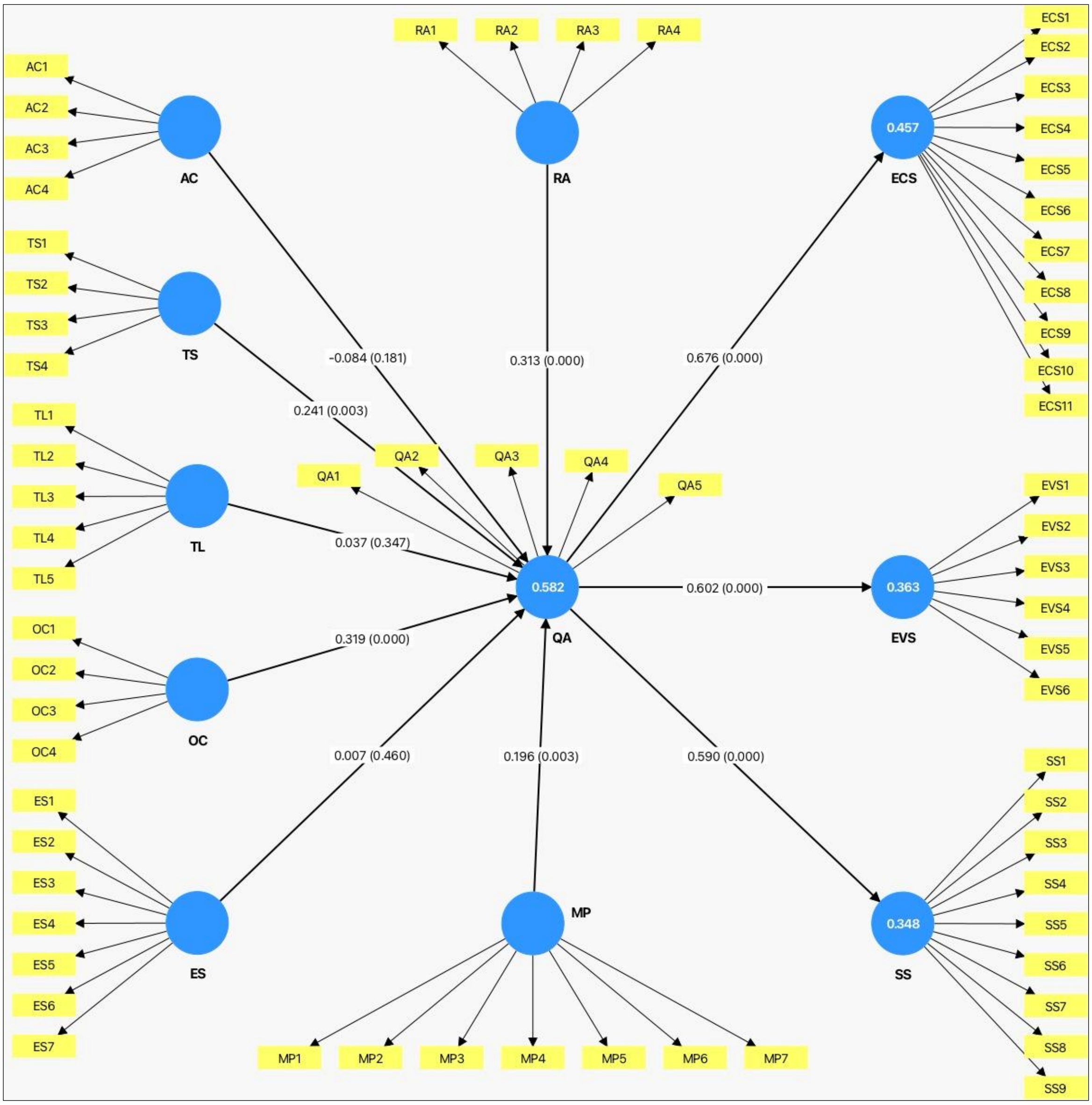
Construct Pair	5%	95.0%
QA <-> MP	0.266	0.505
QA <-> OC	0.576	0.834
RA <-> AC	0.628	0.830
RA <-> ECS	0.425	0.669
RA <-> ES	0.259	0.511
RA <-> EVS	0.330	0.641
RA <-> MP	0.155	0.318
RA <-> OC	0.429	0.683
RA <-> QA	0.550	0.777
SS <-> AC	0.225	0.455
SS <-> ECS	0.493	0.715
SS <-> ES	0.204	0.458
SS <-> EVS	0.493	0.749
SS <-> MP	0.264	0.510
SS <-> OC	0.325	0.582
SS <-> QA	0.505	0.739
SS <-> RA	0.377	0.612
TL <-> AC	0.241	0.475
TL <-> ECS	0.169	0.390
TL <-> ES	0.384	0.680
TL <-> EVS	0.262	0.519
TL <-> MP	0.364	0.642
TL <-> OC	0.300	0.576
TL <-> QA	0.270	0.601
TL <-> RA	0.159	0.302
TL <-> SS	0.220	0.439
TS <-> AC	0.480	0.713
TS <-> ECS	0.329	0.608
TS <-> ES	0.361	0.618
TS <-> EVS	0.405	0.660
TS <-> MP	0.219	0.435
TS <-> OC	0.458	0.720
TS <-> QA	0.575	0.778
TS <-> RA	0.410	0.677
TS <-> SS	0.422	0.679
TS <-> TL	0.515	0.727

Note: Bootstrapping subsamples = 10, 000; Confidence Interval Method = Bias-corrected and accelerated (BCa) bootstrap; Test Type = one tailed; Significance level = 0.05

4.6 Assessment of the Structural Model

After confirming the adequacy of the measurement model, the next phase of the analysis focused on the structural model assessment to examine its explanatory and predictive power. The assessment covered five key criteria including collinearity, the significance of path coefficients, coefficients of determinations (R^2), effect size (f^2), and predictive relevance (Q^2). Figure 4-2 illustrates the graphical output of the structural model generated using SmartPLS 4.1.1.2.

Figure 4-2:
Structural Model



4.6.1 Collinearity Assessment

Table 4-9 presents the collinearity assessment of the structural model. The results indicated that there was no issue at either the indicator or structural levels. All outer model and inner model variance inflation factors (VIF) ranged between 1.160 and 2.969, and between 1.000 and 2.059 respectively, meeting the VIF threshold of ≤ 5.0 and ≤ 3.3 as recommended by Hair et al. (2022).

Table 4-9:
Summary of Outer and Inner Model VIF

Outer Model		Inner Model	
	VIF		VIF
RA1	1.952	RA -> QA	1.877
RA2	2.194		
RA3	1.549		
RA4	1.724		
AC1	1.584	AC -> QA	2.059
AC2	1.800		
AC3	1.753		
AC4	1.683		
TS1	1.639	TS -> QA	2.046
TS2	1.875		
TS3	2.147		
TS4	1.911		
TL1	2.571	TL -> QA	1.891
TL2	2.640		
TL3	1.732		
TL4	2.094		
TL5	1.160		
OC1	1.993	OC -> QA	1.655
OC2	1.531		
OC3	1.584		
OC4	2.073		
ES1	2.455	ES -> QA	1.573
ES2	2.548		
ES3	2.183		
ES4	2.613		
ES5	1.997		
ES6	2.969		
ES7	1.642		
MP1	2.250	MP -> QA	1.424
MP2	2.307		
MP3	2.110		
MP4	2.716		
MP5	2.033		
MP6	2.483		
MP7	1.506		
QA1	2.183	QA -> ECS	1.000
QA2	2.493		
QA3	2.062		
QA4	2.183		
QA5	1.710		
ECS1	2.194	QA -> EVS	1.000
ECS2	2.225		
ECS3	2.350		
ECS4	2.523		
ECS5	1.764		
ECS6	2.625		

Outer Model		Inner Model	
	VIF		VIF
ECS7	2.584		
ECS8	2.353		
ECS9	2.218		
ECS10	2.112		
ECS11	2.315		
EVS1	1.712	QA -> SS	1.000
EVS2	1.910		
EVS3	1.737		
EVS4	1.427		
EVS5	2.233		
EVS6	2.107		
SS1	1.679		
SS2	1.576		
SS3	1.955		
SS4	1.574		
SS5	1.811		
SS6	1.598		
SS7	1.721		
SS8	2.145		
SS9	2.251		

4.6.2 Hypotheses Testing

In this study, there are ten hypothesised paths generated as displayed in Figure 4.2. The significance and relevance of the structural model relationships were evaluated using path coefficient (β) through bootstrapping procedure. According to Hair et al. (2022), for a relationship to be considered statistically significant at a 5% significance level, the p-value must be less than 0.05. In addition, the bootstrap confidence interval for an estimated path coefficient can also determine significance. If the interval does not include zero, it indicates a significant effect, meaning the coefficient is reliably deviated from zero (Hair et al., 2022). Table 4-10 presents the overall summary of hypotheses testing. The following sections provide detailed discussion on each hypothesis testing.

4.6.2.1 Relative Advantage and Quality 4.0 Adoption

H1: Relative advantage of Quality 4.0 technologies is positively and significantly related to Quality 4.0 adoption.

The results indicate that there is a significant positive relationship between the relative advantage of Quality 4.0 technologies and Quality 4.0 adoption, with a path coefficient of 0.313. The t-value of 3.920 and p-value of 0.000 confirm the robustness of this relationship. The one-sided 95% confidence interval (CI=0.193 to 0.455) does not include zero, further supporting the significance. This suggests that greater perceived relative advantage of Quality 4.0 technologies strongly enhance the overall Quality 4.0 adoption.

4.6.2.2 Artificial Intelligence (AI) Compatibility and Quality 4.0 Adoption

H2: AI compatibility is positively and significantly related to Quality 4.0 adoption.

The hypothesised positive and significant relationship between AI compatibility and Quality 4.0 adoption was not supported. The path coefficient is -0.084, with a *t*-value of 0.911 and *p*-value of 0.181, which is above the threshold of 0.05. The one-sided 95% confidence interval (CI = -0.244 to 0.062) contains zero, indicating the effect is statistically insignificant. This suggests that AI compatibility alone may not directly translate into enhanced Quality 4.0 adoption. It also indicates that AI compatibility may play a supporting or enabling role that depends on the presence of complementary organisational and technological conditions, rather than acting as a standalone driver of adoption.

4.6.2.3 Top Management Support and Quality 4.0 Adoption

H3: Top management support is positively and significantly related to Quality 4.0 adoption.

The relationship between top management support and Quality 4.0 adoption is positive and significant, with a path coefficient of 0.241. The *t*-value of 2.743 and *p*-value of 0.003 confirm that the effect is statistically significant. The one-sided 95% confidence interval (CI = 0.106 to 0.397) does not include zero, reconfirming the finding. This demonstrates that top management support contributes significantly to improving Quality 4.0 adoption.

4.6.2.4 Transformational Leadership and Quality 4.0 Adoption

H4: Transformational leadership is positively and significantly related to Quality 4.0 adoption.

The hypothesised path between transformational leadership and Quality 4.0 adoption was not supported. The path coefficient of 0.037, with a low *t*-value of 0.393 and a non-significant *p*-value of 0.347 suggests the path is statistically insignificant. The one-sided 95% confidence interval (CI = -0.135 to 0.177) includes zero, hence confirming insignificance. This implies that transformational leadership may not exert a direct influence on Quality 4.0 adoption. Meantime, it also suggests that transformational leadership may influence Quality 4.0 adoption indirectly, for example through shaping organisational culture or reinforcing top management support, rather than through a direct effect.

4.6.2.5 Organisational Culture and Quality 4.0 Adoption

H5: Organisational culture is positively and significantly related to Quality 4.0 adoption.

Organisational culture was found to have a significant positive effect on Quality 4.0 adoption, with a path coefficient of 0.319. The *t*-value of 3.372 and the *p*-value of 0.000 provide strong statistical evidence. The one-sided 95% confidence interval (CI = 0.163 to 0.472) excludes zero supports the statistical effect of this relationship. This finding highlights the important role of supportive organisational culture in enhancing Quality 4.0 adoption.

4.6.2.6 External Support and Quality 4.0 Adoption

H6: External support is positively and significantly related to Quality 4.0 adoption.

The relationship between external support and Quality 4.0 adoption was hypothesised to be positive, but the results show that the relationship is not significant. The path coefficient of 0.007 with a *t*-value of 0.101 and a *p*-value of 0.460 indicate no effect statistically. The one-sided 95% confidence interval (CI = -0.111 to 0.120) contains zero and hence confirming no significance effect. This finding suggests that while external support may be valuable to the company, it does not directly translate into measurable improvements in Quality 4.0 adoption within the context of this study. It also indicates that external support may function as an enabling or contextual factor that facilitates adoption once internal readiness is established, rather than serving as a primary driver.

4.6.2.7 Market Pressure and Quality 4.0 Adoption

H7: Market pressure is positively and significantly related to Quality 4.0 adoption.

Market pressure positively and significantly influences the Quality 4.0 adoption, with a path coefficient of 0.196. The *t*-value of 2.718 and the *p*-value of 0.003 support this conclusion. The one-sided 95% confidence interval (CI = 0.072 to 0.308) excludes zero, further reaffirming the finding. This finding implies that market pressure pushes manufacturing companies towards adopting Quality 4.0 to maintain their competitiveness and improve corporate sustainability performance.

4.6.2.8 Quality 4.0 Adoption and Economic Sustainability

H8: Quality 4.0 adoption is positively and significantly related to economic sustainability.

The results demonstrate strong positive relationship between Quality 4.0 adoption and economic sustainability performance of the manufacturing company. The path coefficient is 0.676, with a *t*-value of 13.663 and the *p*-value of 0.000 provide significant statistical evidence. The one-sided 95% confidence interval (CI = 0.580 to 0.746) excludes zero supports the statistical effect of this significant relationship. This finding suggests that adopting Quality 4.0 significantly enhances economic sustainability performance of the manufacturing companies within the context of this study.

4.6.2.9 Quality 4.0 Adoption and Environmental Sustainability

H9: Quality 4.0 adoption is positively and significantly related to environmental sustainability.

A similar strong positive relationship is observed between Quality 4.0 adoption and environmental sustainability, with a path coefficient of 0.602. The *t*-value of 10.986 and the *p*-value of 0.000 confirm the strength of this relationship, while the one-sided 95% confidence interval (CI = 0.499 to 0.681) does not contain zero further validates the significance of this positive relationship. This finding implies that Quality 4.0 adoption contributes substantially to environmental sustainability performance of Malaysian manufacturing companies.

4.6.2.10 Quality 4.0 Adoption and Social Sustainability

H10: Quality 4.0 adoption is positively and significantly related to social sustainability.

Lastly, the study displays a significant positive relationship between Quality 4.0 adoption and social sustainability performance of manufacturing companies in Malaysia, with a path coefficient of 0.590. The *t*-value of 10.443 and the *p*-value of 0.000 show strong statistical evidence. The one-sided 95% confidence interval (CI = 0.476 to 0.667) excludes zero, revalidating the robustness of the result. This finding suggests that Quality 4.0 adoption improves social sustainability performance in Malaysian manufacturing sector.

4.6.2.11 Summary of Hypotheses Testing

A total of ten hypotheses were tested as tabulated in Table 4-10. The results supported seven of the hypotheses. The remaining three hypotheses, namely H2, H4, and H6 were not supported. The implications of these findings are further discussed in the next chapter.

Table 4-10:
Hypotheses Testing using Bootstrapping Procedure

Hypothesis	Direct Relationship	Path Coefficient (β)	*t*-value	*p*-value	5% CI	95% CI	Findings
H1	RA -> QA	0.313	3.920	***0.000**	0.193	0.455	**Supported**
H2	AC -> QA	-0.084	0.911	0.181	-0.244	0.062	Not Supported
H3	TS -> QA	0.241	2.743	***0.003**	0.106	0.397	**Supported**
H4	TL -> QA	0.037	0.393	0.347	-0.135	0.177	Not Supported
H5	OC -> QA	0.319	3.372	***0.000**	0.163	0.472	**Supported**
H6	ES -> QA	0.007	0.101	0.460	-0.111	0.120	Not Supported
H7	MP -> QA	0.196	2.718	***0.003**	0.072	0.308	**Supported**
H8	QA -> ECS	0.676	13.663	***0.000**	0.580	0.746	**Supported**
H9	QA -> EVS	0.602	10.986	***0.000**	0.499	0.681	**Supported**
H10	QA -> SS	0.590	10.443	***0.000**	0.476	0.667	**Supported**

Note: Bootstrapping subsamples = 10,000; Amount of results = Complete (slower); Confidence interval method = Bias-corrected and accelerated (BCa) bootstrap; Test type: one tailed; *Significance level = 0.05

4.6.3 Coefficient of Determination (R^2)

Table 4-11 summarises the coefficient of determination (R^2) values for the endogenous constructs in this structural model. According to Chin (1998) guidelines, R^2 values of 0.67, 0.33, and 0.19 are considered substantial, moderate, and weak, respectively. All endogenous constructs in this study achieved moderate R^2 values, which indicate moderate explanatory power. Approximately 58.2% of the variance in Quality 4.0 adoption can be explained by total seven predictors included in the model, followed by about 45.7% variance in economic sustainability can be attributed to Quality 4.0 adoption. Similarly, Quality 4.0 adoption explains approximately 36.3% of the variance in environmental sustainability, and lastly, approximately 34.8% of the variance of social sustainability can be explained by Quality 4.0 adoption.

Table 4-11:
Coefficient of Determination (R^2) Summary

Constructs	R^2	R^2 adjusted	R^2 *Interpretation*
Quality 4.0 Adoption (QA)	0.582	0.557	Moderate
Economic Sustainability (ECS)	0.457	0.453	Moderate
Environmental Sustainability (EVS)	0.363	0.357	Moderate
Social Sustainability (SS)	0.348	0.343	Moderate

4.6.4 Effect Size (f^2)

Table 4-12 presents the effect size (f^2) of the exogenous constructs on their respective endogenous variables. Based on benchmarks recommend by Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and substantial effect size respectively.

For the predictors of Quality 4.0 adoption, relative advantage (f^2 = 0.125), top management support (f^2 = 0.068), organisational culture (f^2 = 0.147), and market pressure (f^2 = 0.064) exert small effects on Quality 4.0 adoption. On the other hand, AI compatibility (f^2 = 0.008) and transformational leadership (f^2 = 0.002) contributed trivial effects, while external support (f^2 = 0.000) showed no effect. The relatively small f^2 is interpreted considering the multi-causal nature of organisational innovation adoption. Within the TOE-based models, adoption decisions are shared by the combined and overlapping influence of technological, organisational, and environmental conditions, rather than by a single dominant determinant. As a result, individual predictors may exhibit modest incremental effect sizes while remaining theoretically and statistically meaningful.

In contrast, the effects of Quality 4.0 adoption on corporate sustainability performance were substantial with economic sustainability f^2 value of 0.843, environmental sustainability f^2 value of 0.569, and social sustainability f^2 value of 0.535. All results are above the substantial effect size threshold of 0.35. This implies that while predictors of Quality 4.0 adoption contribute to the path model at modest level, Quality 4.0 adoption itself is an impactful driver of improving corporate sustainability performance. Once Quality 4.0 is adopted, it functions as an integrated strategic capability that exerts a meaningful influence on corporate sustainability performance across all three dimensions, which explains the substantially larger effect sizes observed. This pattern reflects the asymmetric nature of innovation adoption process, where adoption drivers contribute incrementally, while realised adoption generates more visible organisational outcomes.

Table 4-12:
Effect Size (f^2) Summary

Construct Path	f^2 Value	Effect Size Interpretation
RA -> QA	0.125	Small
AC -> QA	0.008	Trivial
TS -> QA	0.068	Small
TL -> QA	0.002	Trivial
OC -> QA	0.147	Small
ES -> QA	0.000	No
MP -> QA	0.064	Small
QA -> ECS	0.843	Substantial
QA -> EVS	0.569	Substantial
QA -> SS	0.535	Substantial

4.6.5 Predictive Relevance (Q^2)

Table 4-13 presents the predictive relevance summary of Stone-Geisser's Q^2. The results show that Q^2 values obtained for the endogenous constructs are above zero. Hence, it is confirmed that the model has sufficient predictive relevance. However, based on recommendation from Hair et al. (2022), Q^2 alone is not sufficient to examine the predictive power of the model. Thus, PLSpredict results were compared with a linear model (LM) benchmark at the indicator (MV) level using RMSE and MAE as presented in Table 4-13, supported by data presented in Table 4-14. The comparison shows that PLS-SEM predictions outperformed the LM in all indicators. Based on these results, the model is suggested to have high predictive power.

Table 4-13:
PLSpredict LV Summary

Constructs	Q^2 predict	PLS-SEM vs LM Comparison	Predictive Power
Quality 4.0 Adoption (QA)	0.582	PLS-SEM RMSE/MAE < LM	High
Economic Sustainability (ECS)	0.457	PLS-SEM RMSE/MAE < LM	High
Environmental Sustainability (EVS)	0.363	PLS-SEM RMSE/MAE < LM	High
Social Sustainability (SS)	0.348	PLS-SEM RMSE/MAE < LM	High

Note: LV = Latent Variable; RMSE = Root Mean Square Error; MAE = Mean Absolute Error; LM = Linear Model

Table 4-14:
PLSpredict MV Summary

Item	PLS-SEM_RMSE	LM_RMSE	PLS-SEM_MAE	LM_MAE
QA1	1.096	1.227	0.846	0.961
QA2	1.160	1.418	0.899	1.091
QA3	1.085	1.317	0.849	1.046
QA4	1.018	1.192	0.822	0.925
QA5	1.191	1.437	0.947	1.110
ECS1	0.872	1.102	0.715	0.893
ECS2	0.884	1.120	0.732	0.906
ECS3	0.811	0.953	0.659	0.763
ECS4	0.821	0.999	0.697	0.791
ECS5	0.875	1.099	0.730	0.872
ECS6	0.886	1.015	0.734	0.807
ECS7	0.843	0.982	0.695	0.759
ECS8	0.833	1.075	0.669	0.864
ECS9	0.842	1.073	0.705	0.847
ECS10	0.851	1.003	0.694	0.795
ECS11	0.829	1.001	0.693	0.792
EVS1	0.819	0.985	0.663	0.781
EVS2	0.828	0.904	0.688	0.719
EVS3	0.803	0.949	0.633	0.734
EVS4	0.845	0.915	0.706	0.729
EVS5	0.771	0.863	0.612	0.677
EVS6	0.810	0.921	0.662	0.745
SS1	0.873	1.100	0.730	0.907
SS2	0.859	1.212	0.698	0.923
SS3	0.783	0.990	0.627	0.733
SS4	0.995	1.159	0.808	0.929
SS5	0.832	1.021	0.681	0.794
SS6	0.832	1.030	0.667	0.806
SS7	0.893	1.117	0.747	0.891
SS8	0.814	1.090	0.652	0.841
SS9	0.757	0.814	0.617	0.642

Note: MV = Manifest Variable; RMSE = Root Mean Square Error; MAE = Mean Absolute Error; LM = Linear Model

4.7 Chapter Summary

Chapter 4 presents the empirical work of this study. It starts with preliminary data analysis, followed by profiling respondents, analysing measurement items using descriptive statistics, assessing the measurement model, and validating the structural model before drawing implications for Quality 4.0 adoption and its impact on corporate sustainability performance.

During the preliminary data analysis, the survey data are cleaned and screened to ensure data quality before statistical analysis and interpretation. No missing values are observed due to mandatory requirements setting in online survey platform. Two straight lining responses are detected and removed. After the data quality is confirmed, routine checks using skewness and kurtosis confirm acceptable data normality. Common method variance is not a major concern based on Harman's single factor test and full collinearity assessment using variance inflation factor (VIF) for both the outer and inner model. These validations support the subsequent analyses with sufficient confidence.

Respondents are senior quality professionals with large proportions of them hold roles as senior quality executives or quality managers in their companies. Over half report long tenures of more than 10 years. Most worked in large and long-established companies of more than 20 years in operation, especially in the electrical and electronics sectors, and are primarily located in key industrial states such as Selangor and Penang.

Next, PLS-SEM is used to assess the measurement and structural models in SmartPLS 4.1.1.2. The measurement model met conventional standards of reliability and validity check. Most indicators load well on their intended constructs, and multiple tests confirm adequate convergent and discriminant validity. Collinearity checks for the structural model are also within acceptable limits.

Structural model tests highlight four positive drivers of Quality 4.0 adoption, which include relative advantage, top management support, organisational culture, and market pressure. In contrast, AI compatibility, transformational leadership, and external support do not show direct positive and significant effects in this study.

On the other hand, Quality 4.0 adoption is strongly associated with better corporate sustainability performance across economic, environmental, and social dimensions. Overall model performance indicates sufficient explanatory and predictive power, reinforcing the practical significance of the findings.

In short, this chapter concludes that Quality 4.0 adoption is driven primarily by the perceived relative advantage of Quality 4.0 technologies, top management support, an organisational culture that fosters digital quality transformation, and market pressure. It also finds that adopting Quality 4.0 is associated with notable gains in corporate sustainability performance among Malaysian manufacturing companies.

CHAPTER 5:

CONCLUSIONS

5.1 Introduction

Chapter 5 starts with a concise backdrop of the study to reiterate the study's context, objectives, and theoretical perspectives. It is then followed by delivering a focused discussion of findings, centered on the interpretation of Quality 4.0 adoption factors, namely relative advantage, AI compatibility, top management support, transformational leadership, organisational culture, external support, and market pressure. In parallel, it examines the impacts of Quality 4.0 on corporate sustainability performance across economic, environmental and social dimensions. These interpretations correspond directly to and build upon the empirical results reported in Chapter 4. Building on these interpretations, the chapter derives implications for both theoretical and practical aspects, separating conceptual contributions from actionable guidance for manufacturing decision makers and policymakers. It also highlights the limitations of the study to frame the scope and generalisability of the conclusions and identifies directions for future research. The chapter ends with a short conclusion that integrates the key arguments and outlines the study's overall contribution.

5.2 Backdrop of Study

The launch of the Malaysia Madani policy in January 2023 has shifted Malaysia's industrial transformation into a new landscape. Within this overarching compass, the New Industrial Master Plan (NIMP 2030) has prioritised digitalisation to lift manufacturing sector towards value-added, higher productivity, and high-quality employment. Mission 2 of NIMP 2030 explicitly advances a digitally vibrant nation through advanced automation, AI, cloud, and additive manufacturing with substantial approvement and job creation reported between 2021 and mid-2024. Complementing this trajectory, the Malaysia National Artificial Intelligence Roadmap 2021-2025 and recent announcement of the National Semiconductor

Strategy (NSS), plus the newly tabled Thirteen Malaysia Plan (RMK-13, 2026-2030) have signalled policy continuity and growing institutional capacity to integrate digitalisation and AI into industry. The NSS, announced in May 2024, outlines a phased upgrade of Malaysia's semiconductor ecosystem (from current strengths to front-end activities, and advanced fabs), presenting an intent of government to move up the value chain (Lee & Liew, 2024). RMK13, tabled on 31 July 2025, places digitalisation and AI at the center of the country's next five-year development plan, reinforcing national commitments to sustainable growth, high-value jobs, and industrial upgrading (Bernama, 2025b). All these industrial transformation agendas provide the setting and motivation for this research.

Within the national policy context, the manufacturing sector as an important pillar of national growth faces mounting pressures to improve corporate sustainability performance (CSP) across the economic, environmental, and social pillars of the Triple Bottom Line (TBL). Traditional manufacturing systems have long struggled to meet TBL expectations, and stakeholders (public, government, NGOs) are intensifying pressure for better sustainability outcomes. In response, manufacturers are turning to Quality 4.0 (Q4.0), the integration of digital technologies with established quality management practices to reduce waste, optimise resources, and enhance long-terms competitiveness, aligning corporate sustainability goals with operational excellence. Despite policy momentum and early adoption, significant economic, environmental, and social challenges persist, underlining the need for more robust and evidence-based pathways to improve corporate sustainability performance.

Scholars increasingly argue that Quality 4.0 adoption can strengthen corporate sustainability performance across economic, environmental, and social dimensions, but theoretical and empirical gaps remain. Reviews and exploratory studies suggested positive links and competitive benefits for early adopters. However, the field lacks widely accepted adoption and implementation frameworks and offers limited, context-specific evidence, especially for emerging economy manufacturing setting such as Malaysia. It remains unclear which factors drive adoption and how adoption translates into corporate sustainability performance gain empirically. These gaps motivated a focused investigation for manufacturing sector in Malaysia, where policy ambition is high, but organisational capabilities and constraints vary widely, especially between MSME and large companies.

In response to these gaps, this study focuses on medium and large Malaysian manufacturers that have already adopted Quality 4.0, surveying senior quality professionals to obtain practitioner-level insights into Quality 4.0 adoption and its impacts on corporate sustainability performance via a quantitative survey. The research is anchored in clearly articulated objectives, which is to evaluate how seven frequently theorised adoption factors, namely relative advantage, AI compatibility, top management support, transformational leadership, organisational culture, external support, and market pressure shape Quality 4.0 adoption, and to assess how adoption influences corporate sustainability performance consistent with the TBL framing.

The theoretical framing integrates the Technology-Organisation-Environment (TOE) framework and the Resource-Based View (RBV) theory. TOE provides a structured perspective on organisational innovation by positioning key adoption factors in technological, organisational, and environmental contexts, and is well suited to adapting constructs to sector-specific contexts. RBV, through VRIO perspective, conceptualises Quality 4.0 as a strategic capability that when it is valuable, rare, hard to imitate, and built into daily operations can produce sustained performance advantages, including along corporate sustainability performance dimensions. Together, TOE and RBV connect why manufacturing companies adopt Quality 4.0 and how such adoption can produce multi-pillar corporate sustainability outcomes.

This study is significant in two aspects. Theoretically, it advances Quality 4.0 adoption research by testing a unified adoption model in an emerging economy manufacturing setting and by linking adoption to realistic corporate sustainability performance metrics, thereby addressing key gaps in prior research. Practically, it offers actionable guidance to manufacturers navigating post-pandemic recovery, geopolitical uncertainty, and tariff volatility, and provides policymakers evidence to calibrate industrial transformation programmes that accelerate digital transformation towards Malaysia's NIMP 2030 and RMK-13 vision. Positioned at the intersection of national strategy, sectoral struggles, and organisational capability building, this study lays the groundwork for the analyses and interpretations that follow.

5.3 Discussion of Findings

Out of total ten hypotheses tested in this study, seven hypotheses with a direct relationship were supported, and the remaining three were not supported. The following sections summarise the major findings for each hypothesis and provide brief justifications grounded in the theoretical framework and the Malaysian manufacturing context.

5.3.1 Relative Advantage and Quality 4.0 Adoption

The finding shows the relative advantage of Quality 4.0 technologies is positively and significantly related to Quality 4.0 adoption. It is consistent with past studies. Main scholars that studied the diffusion of innovation has positioned relative advantage as a core innovation characteristic and as a consistent predictor of innovation adoption behaviour across different setting (Dearing & Cox, 2018; Rogers, 2003). Within organisational-level setting, relative advantage is also positioned in the technological context of Technology-Organisation-Environment (TOE) framework, which formalises how perceived technological innovation benefits encourage organisations to commit resources to innovation systems (Tornatzky & Klein, 1982). This positioning is reflected in this research model, where relative advantage is explicitly treated as technological driver of Quality 4.0 adoption.

Systematic reviews of Quality 4.0 argue that aligning quality management with Industry 4.0 technologies yields better responsiveness at lower cost and strengthens the decision-making framework and hence gain competitive advantage (Liu et al., 2023; Sony et al., 2020, 2021). When organisations adopt Quality 4.0, the benefits become tangible. Advanced analytics and AI enable tighter process monitoring and control, enhancing quality compliance and conformance, and reducing variability as observed in scrap, rework, yield, and cycle time metrics. Empirical research from Escobar et al. (2021) emphasised that big data and AI-enabled monitoring translate into improved product quality by enabling more accurate and real-time decision loops.

While Quality 4.0 adoption utilises Industry 4.0 technologies, evidence from adjacent Industry 4.0 adoption research supports the same logic. Relative advantage repeated emerges as a significant driver of Industry 4.0 uptake, reinforcing its prominence for Quality 4.0 adoption (Aligarh et al., 2023; Badghish & Soomro, 2024; Shahzad et al., 2023). The most recent empirical research in similar manufacturing setting from Huang et al. (2025) further confirmed that relative advantage of digital technologies positively influences their adoption, which is consistent with this study. This cross-study consistency strengthens the external validity of this hypothesised effect.

In summary, the TOE framing, the diffusion of innovation prediction that perceived relative advantage advances innovation adoption, the operational benefits through which Quality 4.0 technologies deliver visible performance gain, and the study's own significant effect estimate all lead to the same conclusion, which is relative advantage of Quality 4.0 technologies positively and significantly influences Quality 4.0 adoption. Manufacturing companies are more likely to adopt Quality 4.0 technologies when they expect significant gains to both business strategy and operations. It is also important to note that consideration of relative advantage for each Quality 4.0 technologies is also crucial when deciding which technologies to be prioritised and invested in, especially when financial constraints limit the diffusion of innovation amid the fallacy and myth of rapid change in emerging technologies.

5.3.2 Artificial Intelligence (AI) Compatibility and Quality 4.0 Adoption

The hypothesised positive relationship between AI compatibility and Quality 4.0 adoption was not supported in this study. Theoretically, the model locates AI compatibility in the technology context of the integrated TOE framework alongside relative advantage, consistent with DOI arguments that perceived compatibility with existing values, workflows, and needs facilitates innovation adoption (Rogers, 2003; Tornatzky et al., 1990). Accordingly, placing AI compatibility next to relative advantage is theoretical and empirically coherent within TOE/DOI as reported by Badghish and Soomro (2024) and Russo (2024).

Despite the results that AI compatibility does not exhibit a direct effect in this study compared to past studies, these findings echo with recent empirical evidence showing that compatibility is not significant in closely related technology-adoption setting in manufacturing. Huang et al. (2025) in their TOE/DOI study of digital technology adoption in manufacturing firms reported that compatibility does not significantly influence adoption while other factors do. Similarly, Faiz et al. (2024) on digital technology adoption in innovative manufacturing firms find that compatibility does not influence adoption. Together with the results found in this research, these studies suggest that AI compatibility may be enabling rather than driving, which means its effect emerges only when complementary organisational conditions are in place. Enabling refers to AI compatibility reducing perceived integration friction and alignment barriers, without independently triggering adoption decisions. Actual adoption appears to depend more strongly on downstream conditions such as data readiness, governance arrangements, and organisational priorisation. In the context of this study, the non-significant relationship likely reflects that Malaysian manufacturing companies are still prioritising foundational digital capabilities and organisational readiness, such that AI compatibility alone is insufficient to directly trigger Quality 4.0 adoption decisions.

Additionally, the non-significant result is interpreted in view of how AI compatibility was conceptualised and operationalised in this study. Measurement items explicitly captured the perceived feasibility of integrating AI with existing information technology infrastructure, organisational values, attitudinal readiness, and strategic business alignment, reflecting established compatibility dimensions in innovation adoption research. However, perceived integration compatibility does not necessarily imply operational readiness, data maturity, or implementation capability required for AI integrated Quality 4.0 applications. In manufacturing sector where AI deployment depends on advanced data availability, system interoperability, and process standardisation, compatibility perceptions may be necessary, but insufficient to directly trigger adoption decisions. This distinction helps explain why AI compatibility did not exhibit a direct effect, despite being conceptually and operationally relevant.

Besides, when looking at manufacturing sector, even though AI has vast potential and is getting momentum for investment, manufacturers appear to be sequencing their Quality 4.0 technologies investments. They may prioritise foundational technologies and capabilities such as cybersecurity, cloud computing, big data, IoT and system integration before committing to AI-intensive quality applications. Multiple industry reports document this pattern, whereby manufacturers capture value from AI only after building robust data infrastructure and operating models, and leading pilot plants typically scale AI on top of established digital foundations (Behrendt et al., 2021; Coykendall et al., 2024). In addition, the Malaysia National Artificial Intelligence Road Map (AI-Rmap) 2021-2025 frames AI as a long-horizon capability, with strategies that include escalating digital infrastructure to enable AI, governance, and talent pipelines before large scale deployment (Jacob, 2024; MOSTI, 2021). The Malaysia government is also proposing a National AI Technology Action Plan 2026-2030 building on AI-Rmap 2021-2025, as a continuation to scale responsible and high-impact AI adoption, strengthening ethics/governance, and accelerating adoption which is consistent with the organisations investing first in integration, data platforms and security before locking in large AI deployments (As, 2025). In combination, perceived AI compatibility with existing systems may be necessary but not sufficient to trigger Quality 4.0 adoption decisions, diluting its directive predictive power in cross sectional model in this research.

5.3.3 Top Management Support and Quality 4.0 Adoption

Top management support shows a positive and statistically significant relationship with Quality 4.0 adoption in the model. Theoretically, this result is aligned with the TOE framework's organisational context, whereby top management sponsorship acts as a immediate driver that authorises Quality 4.0 initiatives, allocates resources, and coordinate cross functional change (Antony, Sony, et al., 2023; Sony et al., 2021). Narrative literature review from Sony et al. (2020) position top management as an internal change agent within the integrated TOE-DOI perspective, shaping how employees perceive benefits during persuasion and decision stages. The significant path coefficient observed in this study is consistent with that mechanism.

The barriers that hinder Quality 4.0 adoption shows exactly the frictions that top management support is uniquely positioned to resolve. Across empirical evidence, the most frequently cited obstacles include insufficient top management support, ambiguous digital strategy, weak collaboration between quality and IT, skills gaps, and fragmented data and quality systems (Alsadi et al., 2024; Fadilasari et al., 2024; Küpper et al., 2019; Virmani et al., 2024). Top management support can directly address these barriers by setting priorities and funding, by mandating cooperation between quality and IT departments, and by sponsoring skills development so that new strategic capability of Quality 4.0 adoption stick (Antony, Sony, et al., 2023). In short, where adoption fails to take place due to gaps in coordination, capability or confidence, top management support provides the mechanism that aligns functions, unlocks investment, and reduces perceived risk.

Readiness overview by scholars reinforces this justification by showing that top management support and organisational culture repeatedly appear in empirical assessment of Quality 4.0 adoption preparedness, with reviews emphasising that organisations need top management to lead connectivity, analytics, and data management foundations before benefits can be realised (Maganga & Taifa, 2023; Sony et al., 2021; Sony & Naik, 2020; Thekkoote, 2022).

In summary, the findings in this study are consistent with prior studies in which top management support is the organisational vehicle through which organisations overcome known barriers (fundings, skills, integration, change resistance) and assemble the socio-technical conditions that allow Quality 4.0 adoption to happen.

5.3.4 Transformational Leadership and Quality 4.0 Adoption

Although transformational leadership was hypothesised to positively influence Quality 4.0 adoption, the path from transformational leadership to Quality 4.0 adoption was not significant once top management support and organisational culture were included in the same model. This empirical result contrasts with past studies that transformational leaders by articulating a vision, championing change, and enabling learning would directly advance Quality 4.0 adoption (Sony et al., 2020, 2021). Despite prior evidence showing that leadership improves quality programmes and helps overcome Quality 4.0 adoption barriers underpinned the original hypothesis (Virmani et al., 2024), the data does not support a direct positive and significant relationship between two variables.

In the context of this study, this non-significant relationship appears to reflect the dominance of formal organisational mechanism such as governance structure, resource allocation authority, and organisational culture which outweigh leadership style in shaping Quality 4.0 adoption decisions in medium and large manufacturing companies.

Transformational leadership articulates vision and inspires change, but the actual uptake of Quality 4.0 typically requires formal authorisations, investment decisions, cross-functional collaboration, and revised routines which are embedded in top management support and organisational culture. In the context characterised by formal hierarchies and compliance-oriented quality systems which are especially obvious in medium and large manufacturing companies, structural drivers appear to be the decisive predictors. Besides, Quality 4.0 adoption relies on direct and resource demanding mechanisms (e.g. budgets, priorities, governance) captured more directly by top management support and by an innovation adoption oriented organisational culture.

In addition, in Malaysia manufacturing settings, Quality 4.0 adoption typically executed as a quality transformation project lead by a project manager outside of top management circle and lacks direct authority over budgets and cross functional mandates. When it comes to MNC-dominated medium and large manufacturing companies, local innovation adoption often depends on HQ or regional approvals, reinforcing the criticality of top management support. This helps explain the non-significant direct effect of transformational leadership because even an inspiring project leader cannot drive adoption without top management buy-in and endorsement to authorize scope, release fundings, and require inter-departmental cooperation. Without top management sponsorship, extra escalation and effort are needed, which dilutes the project leaders' direct influence on Quality 4.0 adoption.

To summarise, transformational leadership's non-significance does not contradict its relevance. It may indicate an indirect or contingent role rather than a direct and significant effect on Quality 4.0 adoption in this research setting.

5.3.5 Organisational Culture and Quality 4.0 Adoption

Within the organisation context of TOE framework, organisational culture has a positive and significant relationship with Quality 4.0 adoption. The theoretical logic for this finding is straightforward. Within the TOE framework, organisational culture is a condition that shapes how quickly and reliably new quality practices can be embedded. In a Quality 4.0 setting, organisations that emphasise transparency, connectivity, collaboration, rapid and data-informed decisions are better positioned to integrate digital quality tools across vertical, horizontal, and end-to-end processes. In contrast, organisational cultures that resist change or lack cross-functional cooperation impede implementation (Sony et al., 2021). Learning, trust, and cross-unit cooperation enable the integration of quality management systems with analytics capabilities, innovation, and improvement-oriented culture raise overall readiness for Quality 4.0 adoption (Antony, Swarnakar, et al., 2023; Swarnakar et al., 2023; Zulfiqar et al., 2023).

This alignment between theory and empirical evidence is also supported by adoption barriers encountered by manufacturing sector. Quality 4.0 adoption barriers that expose organisational cultural weakness such as change resistance, limited collaboration between Quality and IT, and insufficient learning orientation repeatedly slow or stall adoption progression, alongside financial and leadership constraints (Alsadi et al., 2024; Antony, Sony, et al., 2023; Fadilasari et al., 2024; Swarnakar et al., 2023; Wawak et al., 2023). Against that backdrop, a stronger and more collaborative organisational culture reasonably acts as the direct channel through which digital quality practices are embedded and integrated in daily operation making the positive path coefficient for organisational culture both logical and expected in this study.

In short, an organisational culture of learning, adaptability, and engagement is argued to be a prerequisite for Quality 4.0 adoption. This claim is supported by the empirical evidence reported by various scholars (Antony, Sony, et al., 2023; Sony et al., 2021; Zulfiqar et al., 2023). Practically, the findings indicate the importance of building cross-functional routines and trust, invest in continuous improvement and data-driven decision-making, and institutionalise collaboration between quality and IT teams. As a whole, these steps strengthen day-to-day readiness for analytics, AI-enabled monitoring, and integrated quality systems across production lines, plants, and supply-chain interfaces.

5.3.6 External Support and Quality 4.0 Adoption

Contrary to past studies, the relationship between external support and Quality 4.0 adoption did not support the hypothesis of positive and significant effect. Within the TOE framework, external support is positioned in the environmental context alongside with market pressure. It captures the extent to which assistance from vendors, consultants, industry associations and reference to industrial standards (e.g. ISO9001) can help manufacturing companies adopt and implement new innovation.

Prior empirical evidence suggested that external support will reduce technical uncertainty and transfer know-how to the organisations to drive the Quality 4.0 adoption, particularly on Industrial 4.0 technologies uptake (Jayashree et al., 2022; Khin & Kee, 2022). However, several recent studies echo the non-significant external support pattern as observed in this study regarding Industry 4.0 technologies adoption. Sharma et al. (2024) and Apostoaie et al. (2025) could not confirm the positive and significant impact of vendor support on AI-based technologies adoption. These mixed results could imply such external support from vendors behaving more like enablers than a key adoption factor which is insufficient on its own to drive manufacturing companies in emerging technologies adoption.

In addition, this interpretation fits the adoption barriers discovered in past studies. Recurrent obstacles coming from internal organisational environment include financial constraints, limited top management support, change resistance, skill gaps, weak collaboration between quality and IT, and challenges in data management and integration are more dominant than external support. Under such conditions, external advice or tools can create opportunities, but not able to drive Quality 4.0 adoption or resolve internal adoption barriers. Hence, the direct path from external support to Quality 4.0 adoption is being diluted statistically, while organisational drivers (e.g. top management support and organisational culture) and market pressure carry the effect.

Notably, there is currently no industry or international standard that is directly applicable in this context. In particular, no newly issued international QMS standard documented digitalisation requirements that manufacturers can use as a reference point. Work to address this gap is underway by ISO/TC 176. Several advisory sources anticipate that the new edition of ISO9001:2026 will place greater emphasis on digital transformation, data driven and sustainability practices (Berquand, 2025; King-Davies, 2025). To date, manufacturing companies do not have a definitive ISO standard with explicit digitalisation requirement to rely on.

Overall, the evidence indicates that external support remains valuable, but non-decisive statistically unless it is sequenced after internal readiness is built. In practice, it means visible top management support, collaborative organisational culture, and data governance must be in place so that vendor/consultant/association inputs and emergent standards can be absorbed and converted into day-to-day Quality 4.0 practices. This interpretation is both statistically grounded in the model and consistent with emerging literature on Quality 4.0 and adjacent Industrial 4.0 digital technologies adoptions.

5.3.7 Market Pressure and Quality 4.0 Adoption

Market pressure exhibits a positive and significant association with Quality 4.0 adoption in this research. The result aligns with the TOE framework's environmental context in which external influences such as market dynamics and competitive intensity shape organisational innovation adoption behaviour (Oliveira et al., 2014; Tornatzky et al., 1990). Within this perspective, market pressure functions as an exogeneous factor that increases the perceived necessity of transforming quality management practices when customers, competitors, or suppliers raise the bar. Organisations are more motivated to invest in Quality 4.0 technologies to protect share and meet evolving requirements (Fadilasari et al., 2024; Sony et al., 2021).

The pathway from market pressure to Quality 4.0 adoption is also straightforward in manufacturing setting. Rising customer requirements demand more rigourous monitoring and error prevention, which in turn pushes organisations towards data-rich traceability and faster correction action cycles (Mahin et al., 2024). Competitive intensity and compliance expectations likewise spur uptake of analytics and AI as organisations seek to improve efficiency (Badghish & Soomro, 2024; Min & Kim, 2024). These dynamics are also reflected in the research instrumentation design, which operationalises market pressure via supplier demands, customer expectations, competitive pressures, and industry dynamics which are the very signals that translate into Quality 4.0 adoption prioritisation and resource allocation.

In addition, the importance of market pressure in Malaysia underscored by the country's trade orientation, whereby export trade accounted for 52.8% of total trade in Malaysia as of July 2025 (Ministry of Economy, 2025b). Among them, manufactured goods contributed 46% of total exports and by the dominance of electrical and electronics products at 45.1% of total exports, which ties manufacturing performance closely to external demand and compliance regimes (Ministry of Economy, 2025b). Heightened geopolitical frictions have intensified this pressure. Ongoing Red Sea disruptions have prolonged shipping duration and raised costs and uncertainty for containerised manufactured goods (UNCTAD, 2024). In Europe, the EU Carbon Border Adjustment Mechanism (CBSM) is already in its transitional reporting phase (Oct 2023- Dec 2025) ahead of financial obligations, increasing traceability and carbon-data requirements on exporters (European Commission, 2025). In the United States, Section 301 tariff actions on strategic goods such as EVs, batteries, and semiconductors (United States Trade Representative, 2024), together with stricter UFLPA enforcement elevate due diligence and documentation demands across electronics supply chains even when shipments do not originate from China (CBP, 2025).

In this competitive environment, Quality 4.0 capabilities function as the operational solution whereby manufacturing companies can demonstrate compliance and sustain reliability amid logistic volatility and remain competitive in global and regional oriented market environment. These external conditions amplify the urgency created by market pressure in this model and help explain its positive and significant relationship with Quality 4.0 adoption in Malaysia manufacturing sector.

5.3.8 Quality 4.0 Adoption and Economic Sustainability

Quality 4.0 adoption shows a strong positive and statistically significant relationship with economic sustainability. The finding is theoretically coherent with the Triple Bottom Line (TBL) framing and aligned with empirical evidence that Quality 4.0 adoption improves corporate sustainability performance across all three dimensions (Antony, Sony, et al., 2022; Nenadál et al., 2022)

Quality 4.0 integrates advanced analytics and automation into quality management to generate profit and loss visible gains. Evidence compiled from scholars shows that early adopters achieved higher revenues, reduced cost of quality, improved conformance/performance quality, lower inventory and material costs, and fewer failure-related expenses (Antony, Sony, et al., 2022; Antony, Swarnakar, et al., 2023). These mechanisms include responsive/agile manufacturing systems (Sony & Naik, 2020), mass customization that better matches demand (Park et al., 2017), and automated quality control that raises first-time conformance (Sony & Naik, 2020), complemented by AI-enabled CRM and smarter inventory decisions (Libai et al., 2020).

Contextually, the strength of the path coefficient is reasonable and consistent with the empirical results in which higher and more consistent product quality, reduced scrap and rework, faster and evidence-based decision cycles are precisely the kinds of operational performances that accumulate into economic sustainability at the organisation level (Antony, Sony, et al., 2022; Küpper et al., 2019).

In short, the statistical evidence, explanatory power, and past empirical evidence confirm that Quality 4.0 adoption does enhance economic sustainability in the sampled manufacturing companies in this research. The effect is strong, precise, and theoretically consistent with the TBL framing and with the documented operational pathways providing robust support for H8 in this study.

5.3.9 Quality 4.0 Adoption and Environmental Sustainability

In a similar manner, Quality 4.0 adoption also positively and significantly related to environmental sustainability in the research model. The result is theoretically agreed with the Tripple Bottom Line (TBL) framing that links digital quality management to beneficial environmental outcomes. Quality 4.0 adoption increases resource efficiency and reduces ecological footprint of manufacturing operations. Early adopters demonstrated gains in environmental outcomes and getting real time environmental monitoring data. In practical terms, early adopters do so by minimising waste, scrap, and rework, and by improving raw material utilisation. These are concrete mechanisms that translate adoption into measurable environmental sustainability performance (Antony, Sony, et al., 2022; Küpper et al., 2019; Oláh et al., 2020).

Additionally, continuous digital monitoring across subprocesses reduces variability at source, thereby lowering emissions while conserving materials, energy, and water (Küpper et al., 2019; Oláh et al., 2020). Quality 4.0 practices using Industrial 4.0 technologies also complement the sustainability “ten R” to support cleaner production at scale (Bag et al., 2021). Empirical evidence adds that Quality 4.0 adoption directly reduces scrap, waste, and rework, reinforcing pathway from Quality 4.0 adoption practices to plant level environmental performance (Antony, Sony, et al., 2022).

In short, H9 is supported not only by statistical evidence, but also complemented by a clear operational pathway about how data centric quality transforms resource use and environmental impact via real time monitoring, waste and scrap reduction, and secure environmental data for compliance and improvement (Antony, Swarnakar, et al., 2023).

5.3.10 Quality 4.0 Adoption and Social Sustainability

Lastly, Quality 4.0 adoption shows a positive, and statistically significant association with social sustainability in this study. The result is expected because within the study’s Triple Bottom Line (TBL) framing, Quality 4.0 capabilities are positioned to advance not only economic and environmental outcomes, but also the social dimension of corporate sustainability performance. Moreover, the RBV theory treats Quality 4.0 adoption as strategic capability, which is valuable, rare, inimitable and well organised capabilities that enable corporate responsibility outcomes. Thus, Quality 4.0 adoption should manifest in stronger social performance when these capabilities are embedded in routine work.

According to past studies, early adopters of Quality 4.0 deliver safer, higher quality products and services, enhancing consumer well-being while the same data-driven practices culture a more digitally proficient workforce through upskilling and the development of new roles (Antony, Swarnakar, et al., 2023). Empirical evidence reported improved worker health and safety, fewer accidents, and better workplace conditions, alongside with digitalised HR processes that increase transparency and reduce favourism (Antony, Sony, et al., 2022; Antony, Swarnakar, et al., 2023; Küpper et al., 2019; Sony et al., 2021; Sony & Aithal, 2020).

In the context of Malaysian medium and large manufacturing companies, the strong relationship between Quality 4.0 adoption and social sustainability can be attributed to the sector's emphasis on work force safety, skills developments, and compliance with international customer and regulatory expectations (MITI, 2025). Many Malaysian manufacturing companies, particularly those integrated into global supply chains face increasing pressure from regulators, international buyers, and sustainability frameworks to demonstrate responsible labour practices, transparent processes, and safe working environments (Malaysia Prime Minister's Department, 2025). Quality 4.0 adoption supports these requirements by embedding data-driven monitoring, digital traceability, and standardised quality practices into daily operations, which directly enhance employe well-being, fairness, and workplace safety outcomes.

To conclude, Quality 4.0 adoption improves social sustainability in Malaysian manufacturing companies. The effect is strong, theoretically consistent with the TBL and RBV framing, and grounded in observable organisational drivers of safety, skills, and fairness by which data centric quality practices enhance social outcomes.

5.4 Implications

5.4.1 Theoretical Implications

In general, this research makes several significant theoretical contributions. Firstly, it pioneers the empirical testing of a unified framework linking the TOE dimensions, Quality 4.0 adoption, and corporate sustainability performance in Malaysian manufacturing context. The findings apply the TOE perspective for Quality 4.0 adoption by identifying which technological, organisational, and environmental drivers are most directly linked to adoption and by clarifying how they exert their effects, as demonstrated by statistical tests.

In technological context, the study shows that relative advantage has a positive and significant influence on Quality 4.0 adoption whereas AI compatibility does not show similar positive and significant effects on technology side. AI is still novel for many manufacturing companies in Malaysia. It is a fast-moving technology which companies often delay adoption to reduce risk of locking into tools and interfaces that may soon become obsolete. Formal models of technology adoption under uncertainty predict exactly this wait-and-see behaviour when future performance or costs are evolving quickly (Oliva et al., 2020), which weakens the immediate impact of AI compatibility on Quality 4.0 adoption decisions. Therefore, AI compatibility should therefore be modelled as indirect driver, not a uniformly direct predictor alongside with relative advantage in technological context.

Next, within the organisational context, top management support and organisational culture emerge as significant determinants of Quality 4.0 adoption, whereas transformational leadership style does not exhibit direct effect. Quality 4.0 adoption is a resource intensive (e.g. capital, data, governance, system integration, cross functional coordination) strategic capability which requires resource allocation and a supportive cultural climate that dominates leadership style in shaping the adoption decision. Transformational leadership may inspire people, but does not itself free resources, change KPIs, or alter governance. As a result, its influence appeared to be channeled through the broader organisational mechanisms represented by top management support and organisational culture when adoption decisions are made. Hence, it can be positive, yet statistically insignificant once top management support and organisational culture are in the same model. This pattern also suggests that transformational leadership is more likely to exert an indirect or contextual influence, reinforcing organisational readiness rather than directly determining adoption outcomes. It may therefore play a more prominent role during post-adoption assimilation than for initial adoption decisions in Malaysian manufacturing companies. Further research could formally examine this relationship by modeling top management support and organisational culture as mediating mechanisms linking transformational leadership to Quality 4.0 adoption.

In the environmental context, market pressure coming from industrial setting, customers, competitors or suppliers is a positive and significant key factor of Quality 4.0

adoption, while external support from vendors, consultants or industrial associations is not. Urgent demands from the market create sense of necessity that pushes manufacturing companies to act, but external help on its own has less impact unless the company already develops internal capacity and governance to use that help effectively. Given that most respondents from this study are from large manufacturing companies, this observation is reasonable because those companies typically possess stronger in-house capabilities and formal governance, which means market pressure can be translated into action internally, while external assistance adds value only at the margins. This also signals a boundary condition for generalisation that smaller manufacturing companies with fewer internal resources may rely more on external support, and the effect of such support could be different in MSME-dominated samples. Based on these findings, the refined TOE framework will treat external support as complementary aid, which will be effective when paired with organisational capacity, rather than a standalone driver of Quality 4.0 adoption.

Lastly, the integrated model provides strong empirical evidence for positioning Quality 4.0 adoption as a strategic capability that advances all three pillars of corporate sustainability performance. The effects from Quality 4.0 adoption to economic, environmental, and social performance are all positive and significant statistically. This shifts the focus to how organisations lock in the benefits by turning new strategic capability into everyday routines, standardising processes, and closely tracking performance because once Quality 4.0 is adopted, the gains are much larger than the effect of any single adoption factor that drove adoption in the first place.

5.4.2 Practical Implications

The evidence produces a clear sequence of execution for manufacturing decision makers. Make benefits visible first, because relative advantage is the technological driver that moves adoption which requires capital investment. For Malaysian manufacturing companies operating under tight cost and margin pressures, early visibility of financial and operational benefits is particularly crucial to justify incremental digital investment. It is followed by securing top management ownership and builds a collaborative and data driven digital quality transformative culture that promotes Quality 4.0 adoption. These are the organisational settings that move the innovation from awareness to adoption decision and ideally to full implementation. Finally, harness market pressure to maintain urgency and pacing. Practically, select success cases with direct line of sight to profit and loss, EHS and social performance indicators (e.g. scrap/rework, first-pass yield, cycle time, traceability, waste reduction) and run pilots with pre-agreed baseline. These indicators are especially relevant to Malaysian manufacturers seeking to improve cost competitiveness, export readiness, and compliance credibility within global supply chains. Institutionalise benefits dashboards and ROI business case at workstation, production line, and plant levels so that the relative advantage of Quality 4.0 is repeatedly evidenced in day-to-day operations.

Because top management support and organisational culture are the statistically supported organisational key adoption factors, adoption and implementation should formalise governance and sponsorship. Designate a change management project leader to drive Quality 4.0 adoption, form a cross-functional steering committee spanning Quality, Manufacturing, IT, and EHS, and embed Quality 4.0 targets into performance metrics or balanced score cards. In the Malaysian manufacturing context, such governance mechanisms help overcome fragmented decision-making structures and uneven digital maturity across plants and functions. In parallel, invest in the capability upgrade such as data governance, integration of QMS with MES and analytics, role redesign and e-learning systems that institutionalise data-driven decision that makes adoption sustainable and eventually full-scale implementation. These investments directly address Malaysia's reliance on labour-intensive production by shifting value creation toward higher skilled and data enabled quality roles. In addition, these actions address existing barriers such as skills, collaboration, change resistance, and data fragmentation that the manufacturing sector faced.

On the environmental context, it is recommended to use market pressure to pace and prioritise the Quality 4.0 programme. Align roll-out milestones with customer audits and supplier qualification requirements and employ competitors benchmarks to sustain momentum from pilot to full scale implementation. For Malaysian manufacturers embedded in multinational supply chains, this alignment strengthens audit readiness, traceability, and long-term customer retention. Introduce external support (vendors, consultants, associations) only after internal foundations are in place so that they will act as force multipliers rather than substitutes for internal readiness.

Finally, because Quality 4.0 adoption has large downstream effects on economic, environmental, and social sustainability outcome, manufacturing companies should treat Quality 4.0 adoption as a continuous improvement engine via PDCA cycle, which means measuring the benefits, making them visible, and reinvesting them to sustain momentum of improvement. This reinvestment decision logic supports Malaysian's manufacturers in scaling Quality 4.0 incrementally and reducing implementation risk while accumulating verified sustainability gains. In practical terms, maintain a concise benefits register and use this evidence to prioritise funding from pilot wins to full scale implementation. Linking reinvestment decisions to verified improvements keeps attention on what works and accelerates learning across plants and functions rather than relying on project inputs.

Sustained performance also depends on people and process. Pair deployments with upskilling and reskilling into data and automation roles. Redeploy labour from repetitive or hazardous tasks to higher value analysis and problem-solving roles. This supports workforce resilience and social sustainability outcomes in the Malaysian manufacturing sector, where talent upgrading is critical to long term competitiveness. Digitise HR workflows to strengthen fairness and transparency. At the same time, institutionalise process standardisation because it is the foundation of digital transformation including Quality 4.0 adoption so that gains sustained beyond initial enthusiasm and become part of everyday operations. For boards and policymakers within the organisation, outcome-linked policies that reward visible Quality 4.0 results will accelerate diffusion along strategic capability pathways that generate wider economic, environmental and social value.

Beyond the practical implications for manufacturing decision makers, this study also offers practical contributions for national policy makers. In line with the earlier practical implications for Quality 4.0 adoption at organisational level and aligned to NIMP 2030 and RMK-13, policy should emphasise demand-side pull for Quality 4.0 by embedding data/traceability requirements in public procurement and anchor-firm supplier programmes, so market pressure translates into Quality 4.0 adoption across manufacturing supply chains. Public support should be conditional on organisational readiness, which means eligibility tied to a named executive sponsor, a basic data governance plan, and cross-functional change governance so that funds reinforce the drivers that move Quality 4.0 adoption. To reduce "wait and see" around AI compatibility, policy ought to finance interoperability standards, establish incubator labs, and supervised trial environments for AI integration in quality management among Malaysian manufacturing companies. Incentives should pay for outcomes rather than inputs, rewarding verified improvements in defect rates, first pass yield, cycle time, and energy/water consumption, thereby aligning Quality 4.0 adoption with NIMP's mission-based orientation and RMK-13's governance and digitalisation priorities.

Adoption should recognise different starting points by establishing two tracks, an "accelerate" track for large companies with stronger governance and data foundations, and a MSME "enable" track built around shared services, subsidised readiness audits, and cluster-based peer learning anchored by large buyers. RMK-13's focus on digital trust and cybersecurity should be operationalised and mitigate risk of factory analytics and AI through clear rules on data ownership, privacy, and security, while regional Quality 4.0 hubs (universities, standard bodies, anchor manufacturers) can speed up diffusion of innovation, talent, and method. As a whole, these measures convert relative advantage of Quality 4.0 adoption into visible results, channel top management support and organisational culture into executable improvement programme and amplify market pressure. Based on empirical evidence, this study confirms the key adoption factors that accelerate Quality 4.0 adoption and links them to tangible improvements in corporate sustainability performance.

5.5 Limitation of Study

Despite this study uncovering several valuable theoretical and practical contributions, there are several limitations that should be acknowledged. These limitations relate to the study context and sampling frame, the quantitative and cross-sectional research design, measurement and modelling choices, and the practical challenges of collecting organisational level data. Recognising these constraints helps put the findings in proper perspective and outlines clear directions for future research.

First, the sampling frame of this research is limited to medium and large manufacturing companies registered with Federation of Malaysian Manufacturers (FMM) in Malaysia. The findings should not be generalised to non-FMM manufacturing companies, micro and small manufacturing companies or sectors outside manufacturing. In addition, this study considers manufacturing companies that have already Quality 4.0 adoption. It does not account for adoption rate or maturity level, so early adopters, late adopters and mature implementations are not differentiated, which likely vary in practices and outcomes.

Second, this research uses quantitative survey and a cross-sectional research design. While suitable for testing relationships across a broader sample within limited time frame, it has limitation in looking into strong causal inference in depth and how the relationship evolves over time or within individual manufacturing companies.

Third, the data in this research was collected via a self-administered online survey using self-reported and with single key informant method. Although standard procedural remedies for common method bias were implemented and results indicated that it was not a major concern in this research, other residual biases such as social desirability bias cannot be fully ruled out. Additionally, organisational level data was difficult to obtain as evidenced in this research. Companies reported that they received many survey requests, and they are bound by company policy not to disclose confidential information beyond what is publicly available, which reduced participation and the level of detail provided. As a result, the possibility of non-response bias cannot be fully eliminated, even when mitigation steps are used. This challenge is reflected in the relatively low response rate of 8%, which introduces a potential risk of non-response bias and warrants caution in generalising the findings. Awareness of Quality 4.0 remains uneven across manufacturing companies, and hence understanding of the terms might vary. As a result, some variation in the interpretation of survey items across respondents may exist. Measures of corporate sustainability performance are perception based rather than using audited or secondary data. Cross checking these perceptions with objective indicators and additional informants other than senior quality professionals would strengthen confidence in the estimates.

Fourth, the TOE framework was applied with a selected set of key adoption factors. Other adoption factors (e.g. complexity, trialabilty, observability, digital skills readiness, data integration, digital leadership, financial readiness, regulatory requirement, government support etc.) were not included. On the technology context side, the model treats Quality 4.0 technologies largely as a bundle rather than analysing specific tools (e.g. big data, IoT, simulation, cyber security, cloud computing, autonomous robots, augmented reality, additive manufacturing, system integration, machine learning etc), aside from the separate consideration of AI compatibility. Because some companies may use only one or two of these technologies, technology-specific effects may be masked.

Lastly, the model in this research does not test mediation or moderation relationship, nor conduct measurement invariance or multi-group analysis across subgroups, so potential differences by industry subsector, state or year of operation may be underexplored.

5.6 Direction for Future Research

In general, this study demonstrates that Quality 4.0 adoption strengthens corporate sustainability performance among Malaysian manufacturing companies and can serve as a strategic capability for navigating the era of heightened geopolitical conflict, supply-chain disruptions, and tariff uncertainty. Nevertheless, much remains to be understood about how manufacturing companies can adopt Quality 4.0 effectively. Looking ahead, several recommendations for future research are suggested to address this study's limitations and further enhance its contributions.

First, future research could expand the sampling frame beyond FMM-listed medium and large manufacturers and to include MSMEs, which make up 96.1% of all business establishments in Malaysia (SME Corp, 2025). It will better capture the structure of the economy and the typical resource constraints faced by smaller companies. The initial focus on the sampling frame in this study was intentional because Quality 4.0 adoption is a capital-intensive transformation, and these organisations are more likely to be early adopters as reported by Wawak et al. (2023) and there is no available directory to identify which companies have adopted Quality 4.0 in Malaysia. In parallel, it is also recommended to expand the study beyond manufacturing sector to services sectors. Based on the latest data reported by Ministry of Economy, this sector contributes to the largest share of Malaysia's GDP at 60% in 2024, followed by manufacturing sector at 23.5% (Ministry of Economy, 2025a), This recommendation is to test whether the relationship between Quality 4.0 and corporate sustainability performance holds in service intensive economy settings and to maximise potential spillover effects into the economy's biggest base. Manufacturing sector was prioritised in this study because it is comparatively technology-oriented, compared to other sectors. With this first look at Quality 4.0 early adopters now in hand, subsequent studies can trace how impacts diffuse and how lessons learned from early adopters propagate to late adopters.

Second, in terms of research design, future research may move from cross-sectional study to longitudinal studies if time permits such extension to understand how relationships behave over time, surface implementation pathways inside organisations, and reveal adoption and implementation stage specific challenges from awareness, to pilot, scale up, until institutionalisation. It could provide firmer causal insights and a clearer picture of Quality 4.0 adoption over time. Additionally, adopting a mixed-methods approach such as explanatory sequential of quantitative → qualitative path (QUAN → qual) that combines surveys with interviews or case studies will allow qualitative phase of research to provide in-depth data to supplement the interpretation of the quantitative results, hence lead to more valid and reliable findings.

Third, it is recommended to widen the coverage of respondents by shifting from single-informant to multi-informant designs that include senior quality professional and key decision makers such as operational leaders, EHS and finance managers, IT managers, and C-suite sponsors who authorize budgets and integration. In fact, this recommendation was partially exhibited in this study because responses from key decisions makers were retained even when they fell outside the original specified target group. In addition, further research may triangulate corporate sustainability performance with objective indicators (e.g. audited financial statements, annual reports, audited ESG and sustainability disclosures) to complement perception-based data and reduce residue response biases.

Fourth, future research could offer high-value feedback such as industry benchmarking dashboards (e.g. Q4.0 adoption index, CSP index) together with key actionable takeaways to increase the survey response rate. Another suggestion is to partner with industry bodies and professional associations (e.g. ASQ, IQM) to implement a secure data enclave or to share only aggregated data as a mitigation to address the disclosure concerns from respondents.

Fifth, additional adoption factors could be extended under the TOE framework (e.g. complexity, trialability, observability, digital skills readiness, data integration, digital leadership, financial readiness, regulatory requirement, and government support) to enrich explanatory coverage. Within the technology context, Quality 4.0 technologies could be bundled into technology clusters such as data-centric based (e.g. big data, cloud computing, machine learning, AI, simulation), equipment-centric based (e.g. autonomous robots, additive manufacturing, augmented reality), and enabling layer centric based (e.g. IoT, system integration, cybersecurity), to highlight different impacts of these tools on Quality 4.0 adoption. This is especially worth exploring because many manufacturing companies may adopt only one or two technologies. Analysing clusters may reveal which drivers of adoption matter for different technological footprints.

Lastly, comparative analysis could be performed by industry subsectors, states or years of operation which may reveal other moderation relationships across subgroups to enhance explanatory power of the model. In addition, future research could test whether Quality 4.0 adoption acts as a mediator that transmits the influence of TOE drivers to corporate sustainability performance.

5.7 Conclusion

In conclusion, this research aims to examine how seven key adoption factors, which consists of relative advantage, AI compatibility, top management support, transformational leadership, organisational culture, external support, and market pressure shape Quality 4.0 adoption in Malaysian manufacturing companies, and to evaluate how such adoption influences corporate sustainability performance across economic, environmental and social dimension within a TOE-RBV framing. The study is positioned in Malaysia's current industrial policy push (i.e. NIMP 2030, the National AI Road Map, the National Semiconductor Strategy, and RMK-13), which collectively emphasise digital transformation and AI as drivers for sustainable and high-value industrial upgrading conditions that make Quality 4.0 adoption a timely organisational strategic capability.

Empirically, the measurement model meets conventional reliability and validity thresholds, and the structural model shows adequate explanatory and predictive power. Four key adoption factors, namely relative advantage, top management support, organisational culture, and market pressure emerge as positive and significant drivers of Quality 4.0 adoption, while AI compatibility, transformational leadership and external support do not show direct positive and significant effects in this study. Additionally, Quality 4.0 adoption is strongly associated with higher corporate sustainability performance across the economic, environmental, and social pillars. These results amplified the chapter's central conclusion, whereby Quality 4.0 adoption is driven most by clear perceived relative benefits, visible top management sponsorship, a supportive quality transformation culture, and external market pressures in Malaysian manufacturing sector. Once adopted, Quality 4.0 adoption is linked to strong corporate sustainability gains.

As a whole, these findings directly address the study's overarching aim and the four research questions introduced in Chapter 1. The general objective of examining factors that influence Quality 4.0 adoption and its impact on corporate sustainability has been achieved. The study identifies which TOE factors matter most for direct Quality 4.0 adoption effects in this context and demonstrates that Quality 4.0 adoption is associated with improved corporate sustainability performance. Likewise, the specific objectives are met. Within the technological context, relative advantage but not AI compatibility shows a direct positive and significant effect. Next, within the organisational context, top management support and organisational culture but not transformational leadership has positive and significant relationship. Lastly, within the environmental context, market pressure but not external support is positive and significant when associated with Quality 4.0 adoption. In parallel, Quality 4.0 adoption relates positively and significantly to all three TBL dimensions of corporate sustainability performance.

Contextually, the study demonstrates how the TOE framework applies to Quality 4.0 adoption in an emerging economy manufacturing setting and reinforces the RBV view of Quality 4.0 adoption as a strategic capability with corporate sustainability-linked payoffs. Practically, it offers manufacturers decision makers a focused change agenda, which is to make the economic and operational advantages of Quality 4.0 adoption explicit, especially when comes to which Quality 4.0 technologies to invest to, secure and signal top management commitment, cultivate a culture that supports quality driven digital transformation, and leverage market pressure to overcome inertia. This research also helps them to recognise that compatibility, leadership style and external support may act more as enablers or contingencies than direct drivers in this context. These interpretations flow from the Chapter 4 results and are carried through to Chapter 5's implications and closing synthesis.

Overall, the research questions have been answered and the research objectives both general and specific have been accomplished. In short, the study provides a coherent and evidence-based research of what drives Quality 4.0 adoption in Malaysian manufacturing companies and why that adoption matters for corporate sustainability performance, aligned with the nation's industrial upgrading agenda.

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APPENDICES

Appendix 1:
Questionnaire

Dear Sir/Madam,

Thank you for taking time off from your busy schedule to participate in this survey. We are conducting a study to understand the adoption of Quality 4.0 and the impact on corporate sustainability performance among manufacturing companies in Malaysia.

To participate in this survey, you must have:

i. At least one (1) year of working experience as a Senior Quality Professional representing your current organisation in this survey.

ii. Your current organisation has adopted Quality 4.0 and in operation for more than one (1) year.

Definition:

Quality 4.0: The application of Industry 4.0's advanced digital technologies (i.e. big data, IoT, simulation, cyber security, cloud computing, AI, autonomous robots, augmented reality, additive manufacturing, system integration, machine learning etc.) to enhance traditional best practices in quality management.

All information provided is entirely for the purpose of this academic research.

You will be assured of complete confidentiality and anonymity.

Your participation in this survey is on a voluntary basis and you are free to withdraw from this survey at any time without obligation.

It will only take you 10 to 15 minutes to complete the survey. Your kind participation and full cooperation to complete the questionnaire form as accurately as possible are highly appreciated in making this study a success.

Thank you for your time and valuable contribution.

Yours Sincerely,
Ms. Chan Kit Hie
Universiti Malaysia Sarawak (UNIMAS)
Email: kithiechan.81@gmail.com

SECTION A: DEMOGRAPHIC INFORMATION

1. Please indicate your gender.

☐	Male
☐	Female

2. Please indicate your position in the company.

☐	Senior Quality Executive
☐	Quality Manager
☐	Senior Quality Manager
☐	Quality Director
☐	Other, please specify:

3. Please indicate the duration of your service in your current position at the company.

☐	1 to < 2 years
☐	2 to < 5 years
☐	5 to < 10 years
☐	≥ 10 years

4. Please indicate the type of manufacturing business.

☐	Food, Beverage, and Tobacco
☐	Chemical (including Petroleum)
☐	Fabricated Metals
☐	Machinery & Equipment
☐	Electrical & Electronics
☐	Plastics
☐	Non-Metallic Mineral
☐	Paper, Printing & Publishing
☐	Transport, Vehicle & Equipment
☐	Basic Metal
☐	Rubber
☐	Medical, Precision & Optical Instruments
☐	Textile, Wearing Apparel & Leather
☐	Furniture
☐	Wood & Wood Products, Excluding Furniture
☐	Recycling
☐	Office, Accounting & Computing Machinery
☐	Pharmaceutical
☐	Other, please specify:

5. Please indicate the location of the business.

☐	Johor
☐	Kedah
☐	Kelantan
☐	Melaka
☐	Negeri Sembilan
☐	Pahang
☐	Penang
☐	Perak
☐	Perlis

☐	Sabah
☐	Sarawak
☐	Selangor
☐	Terengganu
☐	WP Kuala Lumpur
☐	Other, please specify:

6. Please indicate the length of the business operation.

☐	< 1 year
☐	1 to < 5 years
☐	5 to < 10 years
☐	10 to < 20 years
☐	≥ 20 years

7. Please indicate the number of employees in the company.

☐	75-200
☐	> 200

SECTION B: QUALITY 4.0 ADOPTION

Instruction: Please indicate your answer for each statement which best describes your opinion using the scale below:

1	2	3	4	5	6	7
Strongly Disagree (SD)	**Disagree**	**Somewhat Disagree**	**Neither Agree nor Disagree**	**Somewhat Agree**	**Agree**	**Strongly Agree (SA)**

1.0 Relative Advantage

		Level of agreement and disagreement						
		SD						**SA**
RA1	Quality 4.0 technology will allow us to better communicate with our business partners.	1	2	3	4	5	6	7
RA2	Quality 4.0 technology will allow us to reduce overall operation costs.	1	2	3	4	5	6	7
RA3	Implementing Quality 4.0 technology will increase the profitability of our business.	1	2	3	4	5	6	7
RA4	Adoption of Quality 4.0 technology will provide timely and more accurate information for decision making.	1	2	3	4	5	6	7

2.0 AI Compatibility

		Level of agreement and disagreement						
		SD						SA
AC1	AI integration in Quality 4.0 adoption is compatible with our information technology infrastructure.	1	2	3	4	5	6	7
AC2	AI integration in Quality 4.0 adoption is consistent with our organisational beliefs and values.	1	2	3	4	5	6	7
AC3	Attitudes towards AI integration in Quality 4.0 adoption in our organisation have been favourable.	1	2	3	4	5	6	7
AC4	AI integration in Quality 4.0 adoption is consistent with our business strategy.	1	2	3	4	5	6	7

3.0 Top Management Support

		Level of agreement and disagreement						
		SD						SA
TS1	Top management enthusiastically supports the adoption of Quality 4.0.	1	2	3	4	5	6	7
TS2	Top management provides adequate resources for the adoption of Quality 4.0.	1	2	3	4	5	6	7
TS3	Top management understands the benefits of Quality 4.0 adoption.	1	2	3	4	5	6	7
TS4	Top management encourages the development of Quality 4.0 technology.	1	2	3	4	5	6	7

4.0 Transformational Leadership

		Level of agreement and disagreement						
		SD						SA
TL1	The management is always on the lookout for new opportunities for the organisation in adopting Quality 4.0.	1	2	3	4	5	6	7
TL2	The management has a clear common view of its final aims of adopting Quality 4.0	1	2	3	4	5	6	7
TL3	The management succeeds in motivating the rest of the organisation in adopting Quality 4.0.	1	2	3	4	5	6	7
TL4	The management always acts as the organisation's leading force in adopting Quality 4.0.	1	2	3	4	5	6	7
TL5	The organisation has leaders who are capable of motivating and guiding their employees in Quality 4.0 adoption.	1	2	3	4	5	6	7

5.0 Organisational Culture

		Level of agreement and disagreement						
		SD						SA
OC1	Our organisation is responsive and flexible in adopting Quality 4.0.	1	2	3	4	5	6	7
OC2	There is a high level of agreement about how we operate in the organisation.	1	2	3	4	5	6	7
OC3	Our organisation has an open and receptive organisational culture in adopting Quality 4.0.	1	2	3	4	5	6	7
OC4	Our organisation has an organisational culture suitable for Quality 4.0 adoption.	1	2	3	4	5	6	7

6.0 External Support

		Level of agreement and disagreement						
		SD						**SA**
ES1	There are technology vendors in the community providing technical support for Quality 4.0 adoption.	1	2	3	4	5	6	7
ES2	Vendors provide valuable assistance during the adoption of Quality 4.0.	1	2	3	4	5	6	7
ES3	Our organisation consults other companies that already implemented Quality 4.0.	1	2	3	4	5	6	7
ES4	Our organisation consults industry associations during Quality 4.0 adoption.	1	2	3	4	5	6	7
ES5	Our organisation employs industry-wide standards to solve Quality 4.0 related difficulties.	1	2	3	4	5	6	7
ES6	Technology vendors provide training on Quality 4.0 technologies.	1	2	3	4	5	6	7
ES7	Technology vendors promote these new technologies by offering free training sessions.	1	2	3	4	5	6	7

7.0 Market Pressure

		Level of agreement and disagreement						
		SD						SA
MP1	Current manufacturing industrial setting is pressuring us to adopt Quality 4.0.	1	2	3	4	5	6	7
MP2	Our organisation is under pressure from competitors to adopt Quality 4.0.	1	2	3	4	5	6	7
MP3	Our organisation adopts Quality 4.0 in response to what competitors are doing.	1	2	3	4	5	6	7
MP4	Our customers are pressuring us to adopt Quality 4.0.	1	2	3	4	5	6	7
MP5	Our suppliers are pressuring us to adopt Quality 4.0.	1	2	3	4	5	6	7
MP6	The relationship with our customers suffers if we do not adopt Quality 4.0.	1	2	3	4	5	6	7
MP7	Adopting Quality 4.0 enhances our competitiveness in the market.	1	2	3	4	5	6	7

8.0 Quality 4.0 Adoption

		Level of agreement and disagreement						
		SD						**SA**
QA1	Effective adoption of Quality 4.0 enables our organisation to reduce production costs.	1	2	3	4	5	6	7
QA2	Effective adoption of Quality 4.0 enables our organisation to increase resource efficiency.	1	2	3	4	5	6	7
QA3	Effective adoption of Quality 4.0 enables our organisation to enhance production flexibility.	1	2	3	4	5	6	7
QA4	Effective adoption of Quality 4.0 fits our organisation well.	1	2	3	4	5	6	7
QA5	Effective adoption of Quality 4.0 is clear and understandable to our employees.	1	2	3	4	5	6	7

SECTION C: CORPORATE SUSTAINABILITY PERFORMANCE

Instruction: Please indicate your answer for each statement which best describes your opinion using the scale below:

1	2	3	4	5
Strongly Disagree (SD)	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree (SA)**

1.0 Economic Sustainability

		Level of agreement and disagreement				
		SD				**SA**
ECS1	The adoption of Quality 4.0 increases the revenue growth of the organisation.	1	2	3	4	5
ECS2	The adoption of Quality 4.0 increases profitability growth of the organisation.	1	2	3	4	5
ECS3	The adoption of Quality 4.0 increases the improvement in terms of sales.	1	2	3	4	5
ECS4	The adoption of Quality 4.0 increases the reputation of the organisation.	1	2	3	4	5
ECS5	The adoption of Quality 4.0 increases the numbers of customers.	1	2	3	4	5
ECS6	The adoption of Quality 4.0 improves product quality.	1	2	3	4	5
ECS7	The adoption of Quality 4.0 decreases customers complaint.	1	2	3	4	5
ECS8	The adoption of Quality 4.0 decreases inventory cost.	1	2	3	4	5
ECS9	The adoption of Quality 4.0 increases production productivity.	1	2	3	4	5
ECS10	The adoption of Quality 4.0 decreases delivery lead time.	1	2	3	4	5
ECS11	The adoption of Quality 4.0 increases new product development.	1	2	3	4	5

2.0 Environmental Sustainability

		Level of agreement and disagreement				
		SD				SA
EVS1	The adoption of Quality 4.0 decreases the wastage from the operations.	1	2	3	4	5
EVS2	The adoption of Quality 4.0 increases the improvement in material usages.	1	2	3	4	5
EVS3	The adoption of Quality 4.0 contributes to the reduction of energy consumption in performing organisational operations.	1	2	3	4	5
EVS4	The adoption of Quality 4.0 contributes to the noise reduction level inside and outside the workplace.	1	2	3	4	5
EVS5	The adoption of Quality 4.0 aligns with the organisational policies that control the air, water, and land emission.	1	2	3	4	5
EVS6	The adoption of Quality 4.0 contributes to hazardous waste reduction from production.	1	2	3	4	5

3.0 Social Sustainability

		Level of agreement and disagreement				
		SD				SA
SS1	The adoption of Quality 4.0 improves training and skills development.	1	2	3	4	5
SS2	The adoption of Quality 4.0 improves corporate social investment.	1	2	3	4	5
SS3	The adoption of Quality 4.0 improves product branding.	1	2	3	4	5
SS4	The adoption of Quality 4.0 increases the number of permanent employees.	1	2	3	4	5
SS5	The adoption of Quality 4.0 increases employee satisfaction.	1	2	3	4	5
SS6	The adoption of Quality 4.0 increases the occupational health and safety of employees.	1	2	3	4	5
SS7	The adoption of Quality 4.0 increases the number of certified suppliers.	1	2	3	4	5

		Level of agreement and disagreement				
		SD				SA
SS8	The adoption of Quality 4.0 increases customer satisfaction.	1	2	3	4	5
SS9	The adoption of Quality 4.0 improves the image of the organisation as a model of good practices among people in the community.	1	2	3	4	5

End of Survey

Thank you for your kind participation.