GREEN RESOURCES, DIGITAL CAPABILITIES, AND FIRM PERFORMANCE: EVIDENCE FROM MALAYSIA'S AUTOMOTIVE INDUSTRY

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By

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ABSTRACT

GREEN RESOURCES, DIGITAL CAPABILITIES, AND FIRM PERFORMANCE: EVIDENCE FROM MALAYSIA'S AUTOMOTIVE INDUSTRY

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The automotive industry has undergone significant transformation due to increasing environmental pressure, particularly in alignment with the Paris Agreement (COP21). In Malaysia, the adoption of electrified vehicles (EVs) has gradually increased, driven by the need for resource-efficient and sustainable solutions. Despite the National Automotive Policies (NAPs) providing strategic direction, challenges persist due to the dominance of internal combustion engine vehicles and linear production approaches that cause persistent carbon emissions. This study investigates the effect of green resources (GR) usage on automotive firm performance (FP), the role of digital technology capabilities (DC) in this relationship, and the mediating effects of DC on firm performance (FP). Underpinning the Resource-Based View (RBV) and Dynamic Capability View (DCV), this study employs a quantitative, explanatory approach using a survey strategy. Data were collected from Malaysian automotive firms that target managerial employees. A sample size of 178 responses was analysed using Structural Equation Modelling (PLS-SEM) with Smart PLS 4.0. These findings reveal that GR and DC significantly enhance FP, with GR exerting a stronger direct effect. Additionally, DC partially mediated the relationship between GR and FP, emphasising its complementary role. From the RBV perspective, green resources are valuable but require dynamic capabilities to be leveraged effectively. The study emphasises the need for continuous investment in R&D, human capital upskilling, and the strategic integration of digital technologies to sustain competitiveness. While this study offers robust quantitative evidence, its regional focus and reliance on survey data limit its broader generalisability. Future research should employ qualitative methods and extend investigations to other sectors to uncover industry-specific challenges and opportunities. Additionally, exploring external mediators and firm size as a moderator would provide deeper insights into the interplay between green resources, digital technology capabilities, and firm performance.

Keywords: Green Resource (GR), Digital Technology Capabilities (DC), Firm Performance (FP), Sustainability, Automotive Industry.

Subject Area: HD28-70 Management. Industrial Management
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“Those who hope in the LORD will renew their strength; they will soar on wings like eagles” (Isaiah 40:31).

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LIST OF ABBREVIATIONS

GHG	Greenhouse Gas
IRP	International Resources Panel (IRP)
CO2	Carbon Dioxide
SDG	Sustainable Development Goals
CE	Circular Economy
ICV	Internal Combustion Vehicles
EVs	Electrified Vehicles (EVs)
IR 4.0	Fourth Industrial Revolution
MITI	Ministry of Investment, Trade and Industry
MIDA	Malaysia Investment Development Authority
MAA	Malaysia Automotive Association
DOSM	Department of Statistics Malaysia
KASA	Ministry of Environment and Water (KASA)
OEM	Original Equipment Manufacturers
SMI	Small and Medium Industries
NxGV	Next-generation vehicles
AACV	Autonomous or Automated and Connected Vehicles
IoT	Internet of Things
NAP	National Automotive Plans
AI	Artificial Intelligence
CPS	Cyber-Physical Systems
BDA	Big Data Analytics
RBV	Resource-based View
VRIN	Valuable, Rare, Inimitable, and Non-substitutable
DCV	Dynamic Capability View
SEM	Structural Equation Modelling
MARii	Malaysia Automotive Robotics and IoT Institute
AMT	Augmented Manufacturing Technology
PLS-SEM	Partial Least Square Structural Equation Modelling
HCM	Hierarchical Component Model
CR	Composite Reliability
AVE	Average Variance Extracted
HTMT	Heterotrait Monotrait ratio
VIF	Variance Inflator Factor
CMB	Common Method Bias
GR	Green Resources
HOC-DC	Higher Order Component – Digital Technology Capabilities
FP	Firm Performance

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CHAPTER 1

INTRODUCTION

1.0 Introduction

This chapter begins with a background of the research study and provides a comprehensive understanding of the research. The background of the study offered a thorough exploration of the research topic and its relevance in the automotive landscape. The next section elucidates the challenges associated with the usage of green resources (renewable materials, water and energy conservation, reuse, recycling and waste management, green technology adoption, and skilled green personnel) in the automotive industry, rather than green manufacturing broadly. It explores how digital technology capabilities play an important role in integrating green resources to address issues and drive sustainable practices in the industry. Subsequently, the research proceeds to articulate the research objectives and questions. The significance of this study is addressed, emphasising its potential contribution to both academic and practical applications. Finally, it concludes with a summary of the chapter.

1.1 Background of the Study

The automotive industry is the cornerstone of a nation's economy, playing a vital role in contributing to employment, technological innovations, and economic growth (Yean, 2021). Over the past few decades, the industry has evolved in tandem with global market demand. In recent years, a notable transformation has emerged in the automotive industry in terms of the necessity for sustainability (Wellbrock et al., 2020). The growing emphasis on sustainability is driven by increasing environmental concerns that necessitate reassessing resource consumption, emission footprints, and ecological impacts. Sustainability is particularly salient in the automotive industry, given its reliance on finite natural resources and substantial contribution to greenhouse gas (GHG) emissions (Szász et al., 2021).

Unlike prior studies that focus on vehicle tailpipe emissions, this study emphasises resource consumption during the manufacturing processes. The manufacturing of conventional vehicles requires approximately 50 different metals, including virgin steel, aluminium, plastics, and critical rare earth elements (Aguilar Esteva et al., 2021; Yahaya et al., 2024). As such, the demand for these materials has grown extensively, becoming a key driver of energy consumption and carbon emissions from industrial processes (Intergovernmental Panel on Climate Change (IPCC), 2023). The direct emissions from the industry sector and indirect emissions from electricity and heat for industrial activities are seen as the major contributors to GHG emissions.

In response, the Paris Agreement was established at the 21st session of the Conference of the Parties to the United Nations Framework Convention on Climate Change (COP21) in 2015, aiming to mitigate climate change by limiting global warming to a threshold of 1.5 °C to reduce emissions by 45% by 2030, and reaching net zero by 2050 (UNEP, 2023). Additionally, most countries have led to a greater commitment to the energy crisis after the COVID-19 pandemic by achieving the net-zero target to ensure energy and economic security.

Over time, greenhouse gas (GHG) emissions have significantly contributed to climate change and global warming. As illustrated in Figure 1.1, GHG emissions decreased by 3.94% in 2020 and increased by 4.05% in 2021. This trend has been steadily increasing since 2021. The annual report of the United Nations Environment Programme (2023) supported that the GHG emissions trend had an unprecedented surge in global carbon dioxide (CO2) emissions after the COVID-19 pandemic. Despite a notable reduction in emissions during the 2020 pandemic, there was no noticeable impact on climate change.

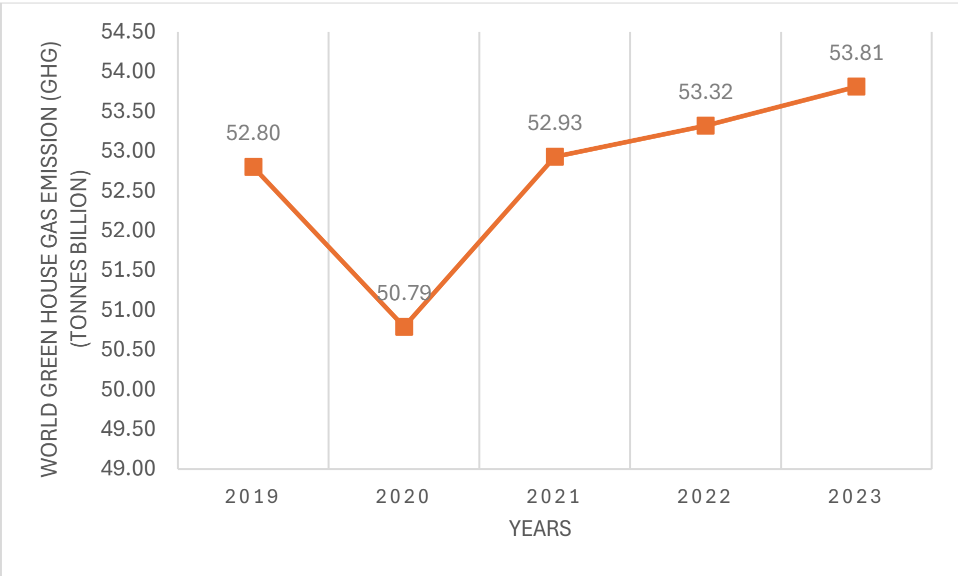


Figure 1.1: World Greenhouse Gas (GHG) Emissions
Source: Ritchie, H. et al. (2020). Greenhouse Gas Emissions. Published online by Our World in Data. Retrieved from: https://ourworldindata.org/greenhouse-gas-emissions.

The increase in GHG emissions was primarily attributed to energy use in the industrial and transportation sectors (UNEP, 2023). Iron and steel production contributed significantly to 7.2% of the total emissions from energy use in the industry (73.2%). Simultaneously, road transport contributed 11.9% to the total transportation emissions (16.2%) (Ritchie et al., 2020). Passenger vehicles are a major contributor to this issue, accounting for approximately 58% of the global transportation industry's emissions and 20% of the overall CO2 emissions (Zhang et al., 2023).

The automotive industry faces mounting pressure to adapt and is at a critical juncture, necessitating substantial changes. The move towards fuel-efficient vehicle strategies to reduce GHG emissions has demonstrated a shift from traditional internal combustion engine (ICE) vehicles to electric vehicles (EVs) (Sopha et al., 2022). Figure 1.2 depicts that the global EV and plug-in hybrid vehicles started to rise drastically in 2020, from 4% to 22% in 2024. The increase reflects the rising demand for EVs since the post COVID-19 pandemic.

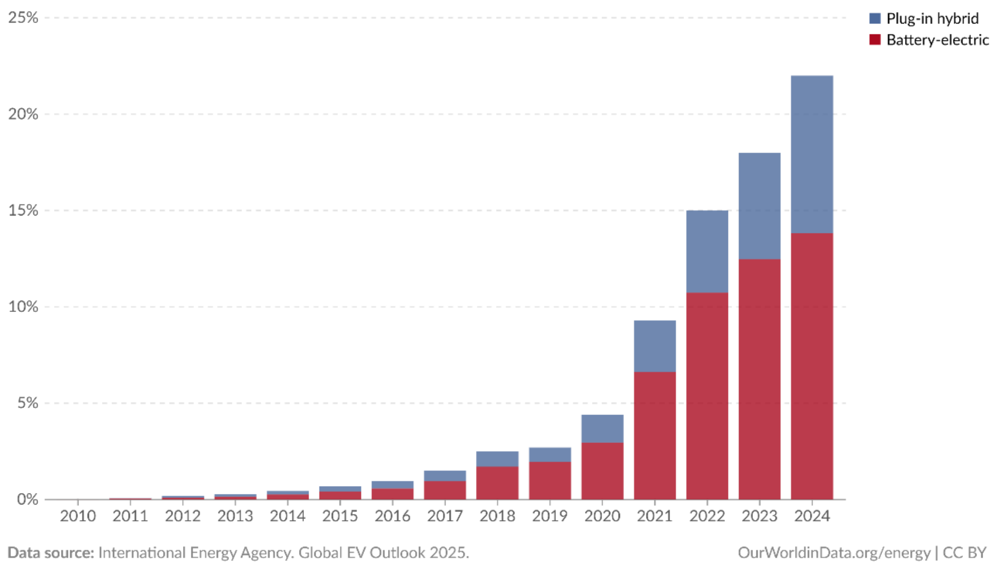


Figure 1.2: World Share of New Cars Sold Battery Electric and Plug-in Hybrid from 2010 to 2024.
Source. Ritchie, H. (2024). Tracking global data on electric vehicles. Published online by Our World in Data. Retrieved from https://ourworldindata.org/electric-car-sales

Consequently, the transition to low-emission vehicles has evolved to address environmental concerns. The focus on the automotive sector's tailpipe emissions was important as the transport sector was among the largest and fastest contributors to average annual GHG emissions, with road transport playing a major role over the past two decades (Intergovernmental Panel on Climate Change (IPCC), 2023). At the same time, the average annual growth in GHG emissions from the industrial sector requires attention. The total direct and indirect GHG emissions from the industrial sector accounted for 34% of the total direct and indirect emissions by sector in 2019 (Intergovernmental Panel on Climate Change (IPCC), 2023). Direct emissions from the industry sector and indirect emissions from the electricity and heat sectors for industry activities were the main contributors to GHG emissions.

The automotive industry is known to be capital-intensive (Yean, 2021) and uses non-renewable and natural resources as essential inputs to transform its products. The industry heavily utilises raw materials such as steel, cast iron and aluminium, plastic, glass, rubber, and fossil and non-fossil energy in vehicle production (Aguilar Esteva et al., 2021; De Abreu et al., 2022). The upstream sector produces the components, parts, and raw materials required by the midstream sector to assemble and manufacture vehicles. Moreover, a steady increase in natural resource consumption raises concerns about potential resource scarcity and the negative environmental impacts of growing vehicle demand (Global Resources Outlook 2019, 2020).

Coupled with the demand for materials by developing countries, this has led to strong growth in new products that influence the industrial processes. Developing countries, such as Southeast Asia, are among the major accelerators of carbon emissions due to industrialisation (Intergovernmental Panel on Climate Change (IPCC), 2023). Furthermore, the automotive industry's conventional manufacturing practices, which employ a linear approach, may contribute to increased emissions and resource depletion (Kifor & Grigore, 2023). Hence, it is necessary to prompt the industry to use materials and energy more efficiently and improve the recovery of materials at the end of a product's life cycle.

The automotive industry needs to focus on the net-zero agenda to reduce carbon (CO2) emissions throughout the entire automotive value chain, from manufacturing to vehicle use. Therefore, the circular economy (CE) focuses on closing the loop of material and energy usage by intensively discussing the revival of natural resources and the reuse of discarded materials and waste (Aguilar Esteva et al., 2021). Leveraging environmentally friendly resources, renewable resources, recycling parts, minimising waste and water usage, and improving energy efficiency at the process level in the automotive industry will potentially curtail the carbon footprint, improve resource efficiency, and achieve sustainability. Moreover, product and process innovation resemble the automotive industry's objective of producing durable and longevity vehicles that optimise material efficiency, reduce costs, minimise waste, and maximise the firm performance.

With the emergence of digital transformation, digital technologies reflect the pervasive nature of digital integration in this transition, enhancing operational efficiency, product performance, and customer engagement (Llopis-Albert et al., 2021). Digital technologies such as Big Data, the Internet of Things (IoT), Cyber-Physical Systems (CPS), Cloud Computing, simulation, robotics and additive manufacturing (Li et al., 2020) are expected to contribute to industry sustainability by reducing waste, improving material efficiency and promoting eco-friendly operations (Valladares Montemayor & Chanda, 2023). Moving towards the circular economy paradigm and achieving net zero carbon emissions, digital technologies are crucial for maintaining competitiveness and productivity while improving organisational performance. From an economic perspective, digital technologies are expected to reduce the operational costs involved in various manufacturing processes (Ghobakhloo & Iranmanesh, 2021), such as in the automotive industry. Digital technologies may bridge and create a closed loop in optimising products and processes to provide a holistic circular economy approach to minimise wastage and improve resource efficiency. This approach significantly contributes to the realisation of sustainable development goals (SDGs), particularly industry, innovation, and infrastructure (SDG 9), and is responsible for consumption and production (SDG 12).

1.2 Malaysia’s Automotive Industry

Malaysia is a developing country in Southeast Asia. The automotive industry contributes nearly RM30 billion to Malaysia's gross domestic product (GDP), and employs approximately 710,000 individuals (MIDA 2022). The automotive industry comprises manufacturers, assemblers, original equipment manufacturers (OEM), and other automotive entities, including Small and Medium Industries (SMI) that produce motor vehicles, parts, and components (MITI, 2023). The industry encompasses two interconnected segments: vehicle manufacturers or assemblers (38 firms) and parts and component suppliers (641 firms), of which approximately 80% of parts and components manufacturers are Malaysian-owned enterprises (MITI, 2023). This study focuses on both segments collectively as the automotive industry, recognising that resource consumption occurs across the entire manufacturing value chain from raw materials processing by suppliers to final assembly by Original Equipment Manufacturers (OEMs).

Figure 1.3 illustrates the total exports and imports of the automotive industry. Automotive product exports increased by 12.8% and 27.3% in 2021 and 2022, respectively, primarily driven by growth in parts and components. Additionally, total imports increased by 30% and 33% in 2021 and 2022, respectively. However, the growth in imports exceeded exports in the automotive industry, which is attributed to the higher imports of parts and accessories for motor and passenger vehicles.

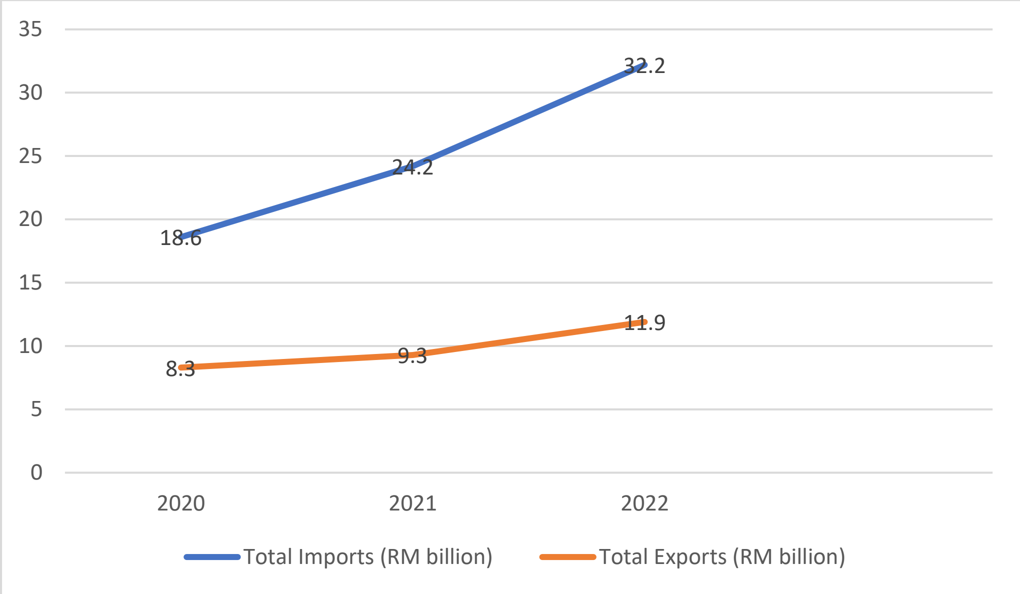


Figure 1.3: Exports and Imports of the Automotive Industry
Source: New Industrial Master Plan 2030: Automotive Industry (MITI, 2023)

Among ASEAN countries, Malaysia's automotive industry ranks third in the production and assembly of motor vehicles, after Indonesia and Thailand (Mohamad-Ali, Ghazilla, Abdul-Rashidl, et al., 2017; Siew Yean, 2021). In 2022, the industry produced 720,658 motor vehicles, representing an increase of 41.6% compared to the previous year, 2021, with 508,911 vehicles (MITI, 2023), wherein passenger vehicle sales dominated the motor vehicle market. The COVID-19 pandemic disrupted motor vehicle production and sales in 2020. Subsequently, figures for production and sales began to recover in 2021 and 2022.

Concurrently, the demand for electrified vehicles among Malaysians has increased significantly, indicating a shift in individual preferences towards environmentally friendly vehicles. Figure 1.4 illustrates that the sales of electrified vehicles (EVs) increased from 2020 to 2022. The annual growth in 2022 recorded an increase of approximately 91.77% compared to 2021.

Furthermore, Energy Efficient Vehicles (EEV) penetration increased linearly from 14 % in 2014 to 88 % in 2019, subsequently decreasing to 82% by 2021, and surging to 93% by 2022, as depicted in Figure 1.5. The COVID-19 pandemic adversely affected EEV penetration in 2021, with recovery observed in 2022.

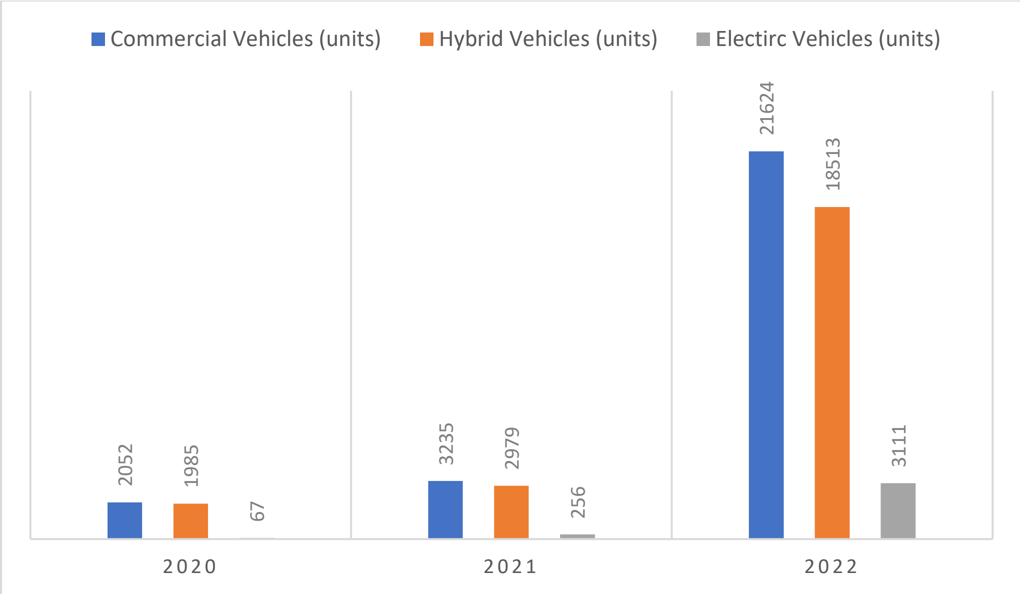


Figure 1.4: Sales of Electrified Vehicles (EV)
Source: New Industrial Master Plan 2030: Automotive Industry (MITI, 2023)

Despite the challenges faced, Malaysia's automotive industry is determined to encourage the adoption of Electric Vehicles (EVs) and see it as an opportunity to reduce emissions (Ministry of Environment and Water (KASA), 2021). The proliferation of EEVs is primarily attributed to governmental incentives, such as tax exemptions and increased awareness of EEV benefits among consumers (MITI, 2023). The positive impact of EEV penetration has positioned Malaysia as a prominent hub for EEV development in the ASEAN region (Ng et al., 2017).

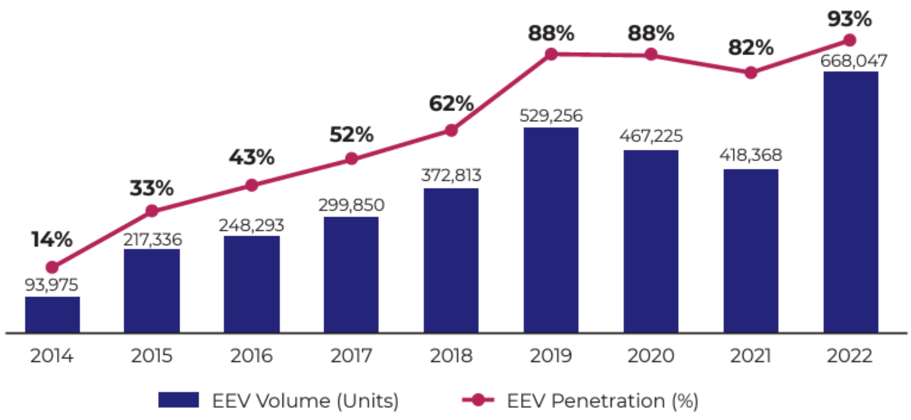


Figure 1.5: Summary of EEV Penetration

Source: Adapted from Ministry of International Trade & Industry (MITI)

The National Automotive Policy (NAP) supports enhancing the automotive industry's competitiveness through green initiatives and practices. The primary aim of the NAP 2014 was to position Malaysia as a hub for EEV by 2020. This strategic direction aligned with Malaysia’s commitment to reducing carbon emissions and promoting energy efficiency, reflecting broader global sustainability goals. The NAP 2014 encouraged the adoption of environmentally friendly practices and stimulated innovation and competitiveness in the automotive sector. Promoting energy-saving vehicle production in Malaysia has demonstrated the efficacy of green innovation in manufacturing processes and product development (Ismail & Zaidi, 2017; Nazir & Shavarebi, 2019).

Nonetheless, the manufacturing phase of vehicles is a substantial and often overlooked contributor to environmental impact. The public attention is often focused on vehicle tailpipe emissions, and manufacturing a vehicle requires different types of resources. Although moving towards the adoption of Electric Vehicles (EVs) is seen as an opportunity to reduce emissions, the shift does not eliminate manufacturing resource usage. The EEV vehicle batteries still require significant material input and manufacturing energy (Aguilar Esteva et al., 2021). Thus, green resource usage remains critical regardless of vehicle-powered technology. As such, the GHG emissions in Malaysia have been rising since 2020, as shown in Figure 1.6. Similar to the world GHG emissions trend, the COVID-19 pandemic slowed emissions, and the trend surged to high levels during the post-pandemic period. Critically, in Malaysia, the industry sector contributed 33% of the total final energy consumption in 2022, followed by the transport sector, dominated by fuel combustion vehicles at 32% (International Energy Agency, 2022). The transport emissions occur during vehicle use and are influenced by consumer behaviour, unlike the manufacturing emissions, which are directly controllable by automotive firms through resource efficiency measures.

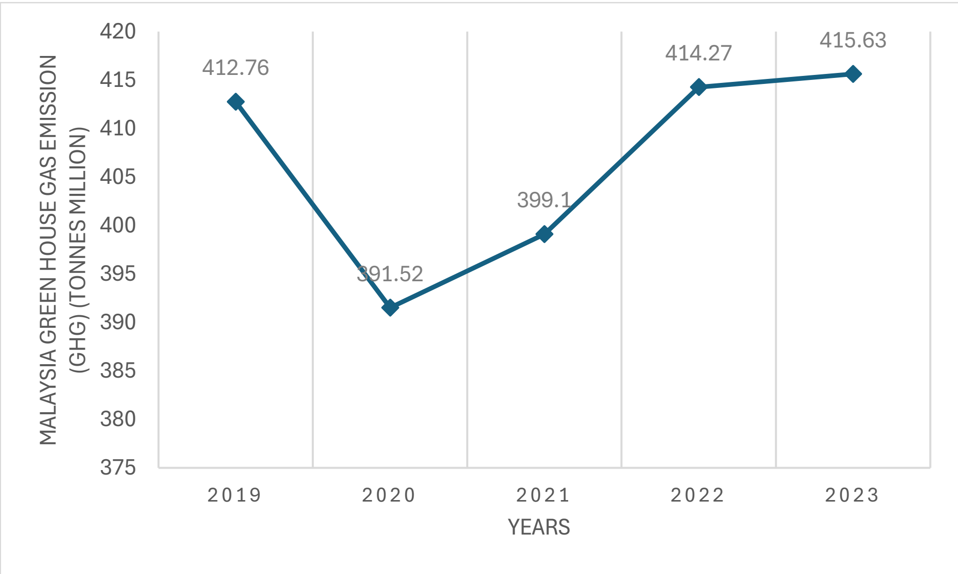


Figure 1.6: Malaysia's Greenhouse Gas (GHG) Emissions
Source: Hannah Ritchie, Pablo Rosado, and Max Roser. (2020). Greenhouse Gas Emissions. Published online at OurWorldinData.org and retrieved from: https://ourworldindata.org/greenhouse-gas-emissions.

Despite global shifts towards a circular economy, Malaysia's automotive industry continues to operate predominantly on a linear "take-make-dispose" model, with practical recycling being almost absent and widespread use of virgin materials (Yahaya et al., 2024). Besides that, there is a lack of law and comprehensive management for end-of-life vehicle recycling (Jamaluddin et al., 2022). Consistently, Malaysia is still facing a growing end-of-life vehicle problem. In 2023, surprisingly, 9,267,376 vehicles on the road were more than 10 years old (Mohamad-Ali et al., 2024), creating urgent resource recovery challenges.

Thus, in 2022, Malaysia only achieved a 1% reduction in emissions, as highlighted in Malaysia's 2023 National Energy Transition Roadmap (Ministry of Economy, 2023). Under the Kyoto Protocol in 2022 and the Paris Agreement in 2016, Malaysia ratified and communicated the country's Nationally Determined Contributions (NDC), intending to reduce 45 % of gross domestic product emissions intensity by 2030 in the base year 2005 (KASA, 2021) and achieve net zero by 2050 (Shamsul Azlan et al., 2023). Malaysia is committed to reducing and neutralising carbon emissions to address the climate change issue.

However, the call for policy adoption at the firm level, particularly among parts and components suppliers, remains inconsistent (Raziff et al., 2024; Yahaya et al., 2024). The concept of green resources directly addresses these manufacturing-phase challenges. The green resources are known as tangible and people-based assets that firms utilise to achieve resource efficiency. This approach will enhance resource management, subsequently improving firm performance that emphasises the beneficial effects of green innovation on production processes, products, and organisational management, resulting in improved product life cycles, pollution prevention, and resource efficiency. The automotive sector's dedication to sustainability is exemplified by its use of eco-friendly materials (Kasava et al., 2020) and the enhancement of talent through skill, knowledge, and experience rejuvenation (Rahim & Zainuddin, 2019). These efforts contribute to the industry's capacity to enhance sustainability and performance.

The National Automotive Policy (NAP) 2014 and 2020 have promoted the green initiatives, circular activities, and Industry 4.0 technology adoption (MITI, 2020, 2023). As the automotive sector evolved and embraced the Fourth Industrial Revolution (IR 4.0), Malaysia responded by adopting advanced technology for the progressive automation of production processes. The national mission continued to shape Malaysia's automotive industry in the digital revolution, enabling Malaysia to position itself as a regional leader in manufacturing to ensure a sustainable automotive industry (MITI, 2020). To ensure sustainability, circular economy activities such as recycling, reuse, and remanufacturing were promoted to enhance resource efficiency in the automotive industry.

Thus, integrating with advanced digital technologies such as Big Data Analytics (BDA), Artificial Intelligence (AI), Augmented Reality, Additive Manufacturing, System Integration, Autonomous Robot, Advanced Material, Cloud Computing, Cyber-Physical Systems (CPS), and the Internet of Things

(IoT) enable the industry to operate the production and product phases intelligently and focus on developing automotive industry capabilities within a comprehensive ecosystem to enhance resource efficiency (MITI, 2020). Such optimisation in design and production processes will allow the manufacturing processes to integrate vertically and horizontally efficiently, which increases resource utilisation, enhances environmental quality, reduces production expenses, and elevates firm performance (Tan et al., 2019).

In conclusion, the automotive industry's ongoing pursuit of carbon emissions reduction and sustainability remains a priority. The strategic integration of resource efficiency with digital technologies employing environmentally friendly resources to achieve resource effectiveness further enhances the performance of firms within the automotive sector.

1.3 Problem Statement

The Malaysian automotive industry faces significant challenges in optimising green resources usage to improve firm performance. The dominance of internal combustion engine (ICE) vehicles on the road has led to significant emissions (MITI, 2023). Clearly, the Malaysian automotive sector still focuses on manufacturing ICE vehicles due to consumer preference, with a step into next-generation automation. As such, the automotive industry is interlinked with the backwards and forward subsectors, which, through specific activities and diversity of components and resources consumed, have a significant impact on the environment at each stage of life.

The manufacturing of vehicles consumes large amounts of water, natural resources and energy, which contributes to adverse effects on carbon emissions. Virgin steel and aluminium are the two largest components, followed by plastics, as well as eco-friendly materials and critical and rare earth elements (Aguilar Esteva et al., 2021). It is crucial to reduce consumption through material use efficiency, substitutions or promoting end-of-life recovery to reflect sustainability and optimisation of green resources to reduce the significant burden on GHG emissions. Although numerous past studies have explored sustainability in the automotive and broader manufacturing sectors (Alos-Simo et al., 2020; El-Kassar & Singh, 2019; Giampieri et al., 2019, 2020), limited empirical evidence exists specifically on how green resource usage affects firm performance in the Malaysian automotive industry. The level of sustainability implementation across the automotive industry as a whole still requires more investigation. Existing studies have focused broadly on "green manufacturing practices" rather than focusing on the specific effect of resource consumption efficiency (Pathak et al., 2021; Wen Chiet et al., 2019). The board focused on practices, policies, and certification does not detach the resource efficiency contribution. Consequently, focusing specifically on green resource usage enable to measure how firms use and control resources to achieve resource efficiency.

Since the post-pandemic period and the shortage of electronic components and materials, the interest in shifting to circular economy practices in the automotive industry has gained attention globally (Kifor & Grigore, 2023; Okorie et al., 2023; Tong et al., 2024) and in Malaysia (Jamaluddin et al., 2022; Mohamad-

Ali et al., 2024; Raziff et al., 2024; Yahaya et al., 2024). However, there have been widespread practices of green manufacturing and production in the automotive sector, yet they have been unable to address GHG emissions and remain sustainable. Thus, the circular economy remains ambiguous in the context of Malaysia's automotive industry, particularly concerning material utilisation efficiency. Additionally, there is no specific law and a lack of comprehensive management relating to end-of-life recycling, which leads to inefficient use of green resources (Jamaluddin et al., 2022). Due to the high cost embedded along the eco-industrial chain in remanufacturing and the uncertain price of the recycled material market, there is a motivation for firms to seek to utilise raw materials as seen as inexpensive.

Thus, the firms will utilise the resources that produce economic value. The reason is that resources must produce economic value to be considered strategically valuable (Barney, 1991). Thus, green resource usage may improve environmental performance but would not be sustained over time if not improve firm performance. Green manufacturing practices significantly enhanced operational performance (Abdul-Rashid, Sakundarini, Ariffin, et al., 2017; Bellantuono et al., 2021), but it has less effect on financial performance (Nureen et al., 2023). Consequently, green resources will consistently improve operational performance but only transform to financial returns when the market conditions reward green differentiation or regulations internalise the environmental costs (Setiawan et al., 2025).

Despite numerous emission challenges, zero-carbon manufacturing in the automotive industry can be a viable solution for long-term sustainability. Hence, in a broader approach, a zero-carbon economy can be achieved when Malaysia's material input becomes 100% sustainable and non-finite resources are utilised. However, as the industry is currently dependent on green manufacturing practices, the utilisation of green resources along with the deployment of digital technology in the automotive industry can enhance resource efficiency through thorough data analytics (Syed, 2023). Moreover, digital technology such as big data is able to provide transparency and traceability in material and energy flow, which enables automative firms to plan and monitor their resources (Yu et al., 2022). Additionally, numerous past studies discussed the role of digital technologies' capability in influencing the efficient utilisation of resources in manufacturing, which can enhance firm performance (Belhadi et al., 2020; Y. Li et al., 2020).

Integrating a smart production process in the conventional industrial process will help the automotive industry to reduce production cost, minimise emissions and water pollution (Thomas & Mishra, 2024). This adoption will enable the industry to be more connected and integrated holistically through processes, products, and services (MITI, 2023). The drive towards decarbonisation will gain momentum as green resources are integrated with digital technologies. However, the role of digital technology capabilities as a mediator between green resource usage and firm performance remains scarce, particularly in the Malaysian automotive context. Digital capabilities had an insignificant direct effect on firm performance but significant indirect effects through agility, suggesting mediation is required (L. Li et al., 2022).

Sustainability, green manufacturing, and lean manufacturing have been widely studied in the automotive sector (Abdul Ghafar & Mohd Razali, 2022; Giampieri et al., 2019b; Kasava et al., 2020; Maldonado-Guzmán et al., 2023; Syed, 2023; Szász et al., 2021; Wellbrock et al., 2020; Zainuddin et al., 2019) as well as digital technologies, Industry 4.0, and Smart Manufacturing (Beg et al., 2022; Llopis-Albert et al., 2021; Rahim & Zainuddin, 2019; Rizvi et al., 2023; Syed, 2023; Valladares Montemayor & Chanda, 2023), the pandemic highlighted the importance of a holistic, sustainable approach in improving green resource consumption and efficiency to move toward a zero-carbon economy. The transition to the circular economy has recently become important in the post-pandemic period (2021-2024), that driven efforts to close the loop through digitalisation (Aguilar Esteva et al., 2021; De Abreu et al., 2022; Madrid, 2023; Khan et al., 2022; Kifor & Grigore, 2023; Okorie et al., 2023; Rizvi et al., 2023; Sopha et al., 2022; Thomas & Mishra, 2024).

Although still in its infancy among developing countries, particularly Malaysia, studies on recycling, remanufacturing, and end-of-life vehicles are gaining attention (Jamaluddin et al., 2022; Mohamad-Ali et al., 2024; Raziff et al., 2024). Most of the existing Malaysian studies focused on large Original Equipment Manufacturers (OEM) firms (Habidin et al., 2018), and an exploratory study (Yahaya et al., 2024) that lacks causal evidence on green resources on firm performance. The supplier segment that is owned by 80% of Malaysian is particularly under researched, despite Small and Medium Enterprises (SMEs) facing resource constraints and capability gaps compared to large OEMs (Azman & Ahmad, 2023; Gohoungodji et al., 2020).

This study is significant for providing insight into the complexity of current green resource utilisation and the interrelationship between the role of digital capability and performance in automotive firms. Although it is at an early stage, this study indirectly contributes to advancing circular economy practices within the automotive industry. Therefore, it is important to understand resource efficiency, particularly in terms of resource consumption, as it requires a clear perspective on how digital technologies are integrated into industrial processes.

This study provides empirical evidence of green resource usage in automotive firms across products and industrial processes. These include the use of renewable, eco-friendly, and recycled materials and waste, efforts to save water and energy, deployment of technology to reduce pollution and emissions, and the role of skilled and experienced workers in improving resource efficiency. While past studies have explored the concepts of the circular economy paradigm in the automotive industry (Jamaluddin et al., 2022; Raziff et al., 2024; Yahaya et al., 2024), few have examined the causal interrelationships. As a result, this study will provide an in-depth understanding of how internal resource efficiency can be improved through the integration of digital technology capability and how this, in turn, can unlock economic spillover benefits for automotive firms.

1.4 Research Question

Based on the issue of green resources, the role of digital technology capabilities, and the performance of the automotive industry, the research question imposed in this paper are:

1) Does green resource usage affect the firm performance in Malaysia's automotive industry?
2) Does green resource usage affect the role of digital technology capabilities?
3) Do digital technology capabilities affect firm performance in Malaysia's automotive industry?
4) Do digital technology capabilities mediate the relationship between green resources and automotive firm performance?

1.5 Research Objectives

While answering the above research questions, this study aims to achieve the following objectives:

1) To investigate the effects of green resource usage on automotive firm performance.
2) To investigate the effects of green resource usage on the role of digital technology capabilities of automotive firms.
3) To examine the effects of digital technology capabilities on automotive firm performance.
4) To examine the mediating effects of digital technology capabilities on the relationship between green resource usage and automotive firm performance.

1.6 Significance of the Study

The significance of the study discussed the overall contribution to the body of knowledge.

Theoretical Significance

A unique resource bundle that adds value to the firm is essential for achieving competitive advantage in dynamic markets. Firms with such characteristics can stand up and compete with their competitors. External pressures require the firm to reform the internal structure, which can be successful if the firm acquires imitable and non-substitutable resources. Similarly, the Resource-based View (RBV) standpoint argued that resources may be static over time due to the Industrial Revolution (Barney, 1991). The revolution requires firms to acquire and change existing resources and integrate them with their core competencies to sustain their competitiveness and accomplish better firm performance. In such cases, the relationship between the use of resources, especially green resources, and firm performance remains ambiguous due to the limited past studies. Thus, exploring an automotive firm's micro level, focusing on the use of green resources and their effect on firm performance, will provide new knowledge on resource efficiency and sustainability through theory-driven empirical results.

In addition, building a dynamic firm capability with its unique resources can accelerate firm performance (Teece, 2018). The core competencies portray the firm's capability to use, change and transform the resources to achieve economic scale and improve environmental performance. The competency is supported by combining various digital technologies that add value to the firm by developing its core organisational capability to face environmental challenges (Haseeb et al., 2019). In a similar vein, the firm's capabilities depend on the sector, activity, and strategy to leverage the benefits internally and externally. Hence, this study is expected to provide a fruitful understanding by clarifying the role of dynamic digital technology capabilities as a predictor of green resources and firm performance.

Managerial Significance

This study will provide substantial information on the current state of green resource usage, the role of digital technology capability in automotive firms, and its contribution to firm performance. Similarly, this study sheds light on the managerial ability to efficiently manage green resources by configuring digital technology to spur firm performance.

Automotive firms will enhance their existing green strategies by building robust digital technology capabilities through organisational, technological, and environmental factors. In the same vein, firms can identify their green resources and accelerate optimisation through digital technologies to achieve better and improved firm performance (Gupta et al., 2020). In addition, managers must be committed and support the firm's green initiatives and digital technology assimilation. The automotive firm may reach out for government assistance and university collaboration to enhance green and digital technology innovation to uplift the firm performance. Therefore, automotive firms can identify the training and recruiting of experienced and technical experts to work together to achieve the firm sustainability. Thus, strategies for using green resources and building a proper facility of digital technologies to promote sustainability in achieving net zero carbon emissions and emerging into circular economy production. Accelerating firm performance by meeting economic and environmental outcomes is crucial in adopting digital technology.

Scholars Significance

This study proposes a conceptual framework grounded in the Resource-Based View (RBV) and the Dynamic Capability View (DCV). By addressing the limited past research on green resource usage, digital technology capabilities, and firm performance, the study will provide a better roadmap for scholar to explore in future.

As a cross-sectional study, this study provides better insight into the relationships that contribute to the existing body of knowledge. The use of structural equation modelling (SEM) allows for the simultaneous analysis of the proposed framework to provide a strong methodological approach. This approach highlights the mediating role of digital technology capability in linking green resource usage to firm performance, which elaborates on their critical importance in enhancing sustainability and competitiveness. Integrating theoretical underpinnings with advanced analytical techniques, this study provides academic understanding and practical implications for firms to optimise resource efficiency and performance in competitive environments.

Policy Makers Significance

This study is important to provide policymakers with a better understanding of strategies to promote sustainable practices within the automotive sector. Hence, this study aligns with the United Nations' Sustainable Development Goals (SDG) and supports the efficient utilisation of green resources to achieve sustainability. This will inspire the firms to align their strategies and targets with those presented in the National Automotive Policy (NAP). The policy emphasised green initiatives and digital transformation to encourage the automotive industry to enhance digital technology capabilities to accelerate efficiency in optimising green resources and achieving better firm performance. Moreover, automotive firms can collaborate with related institutions such as Malaysia Automotive Robotics and IoT Institute (MARii) to strengthen their competitive edge and gain sustainability. This partnership can foster innovation, support technology adoption, and equip firms with the tools needed to remain agile and competitive in changing industry circumstances.

1.7 Scope of Study

This study focuses primarily on the automotive industry in Malaysia, which is the primary area of investigation. The selection of the automotive industry is due to the fact that this sector encompasses several sub-sectors that are equally important to the expansion and development of the economy. The manufacturers, assemblers, and component and parts companies involved in the automotive industry are the primary subjects of this study. The automotive industry embraces Industry 4.0 technologies and disseminates the technologies throughout the industry to experience the smart factory concept (Bigliardi et al., 2020). Many past studies have focused on large automotive manufacturers, and it is important to investigate the industry as a whole to better understand resource usage and digital technology capabilities (Gohoungodji et al., 2020).

1.8 Operational Definition

1.8.1 Green Resources

Teece (2014) describes that factors of production are "undifferentiated" inputs that firms will acquire and transform into unique and inimitable firm-specific resources. El-Kassar and Singh (2019) describe resources as tangible and intangible, and people with noteworthy value when combined. Likewise, green resources refer to using resources in production that minimise the environmental impact and achieve efficiency in resources (Ng et al., 2017). The optimisation of the consumption of green resources and industrial emissions reflects the firm's sustainable manufacturing assessment. The green resources in the study consist of eco-friendly materials, waste and recovery materials, water and energy conservation, and green technology and technical skills. Green resources are used in industrial processes to transform green products that minimise carbon emissions (Gohoungodji et al., 2020). The raw materials used as resources in green manufacturing are renewable (Barney, 1991). Using raw materials to turn into waste materials is considered a natural resource (Petraru & Gavrilescu, 2010) and can be renewable (Wei et al., 2008). Pollution prevention can be minimised by achieving efficiency in raw material usage, energy, water, and other resources that lead to economic savings. Positioning employees with skills and talent that connect with sustainability contributes to firm performance (El-

Kassar & Singh, 2019).

1.8.2 Digital Technology Capabilities

Digital technologies are used to transform the digitalisation manufacturing process (Hamdi et al., 2019). Based on National Automotive Policy 2020, digital technology includes Big Data Analytics (BDA), Artificial Intelligence (AI), Augmented Reality, Additive Manufacturing, System Integration, Autonomous Robot, Advanced Material, Cloud Computing, Cyber-Physical Systems (CPS), and the Internet of Things (IoT) (MITI, 2020). The digital technology capabilities adopted in the Pavlou and El Sawy (2022) framework consist of sensing, learning, integrating and coordination.

1.8.3 Firm Performance

Newbert (2007) described profit as earning above-normal profit from utilising resources to produce demanded products. Firm performance is the relationship between a firm’s resources and their utilisation by an organisation to improve financial and operational conditions (Newbert, 2007). Firm performance consists of financial performance measures, such as profitability, sales growth, market share, and return on investment (Khan et al., 2022; Latifi et al., 2021; Yu et al., 2022). While, operational outcomes measure cost reduction, quality improvement, production efficiency, waste reduction, and delivery speed (Abdul-Rashid, Sakundarini, Ariffin, et al., 2017; Nureen et al., 2023; Varela et al., 2019). The findings of this study confirm whether green resource usage positively influences firms' performance.

1.9 Chapter Layout

This chapter is structured into five chapters, contributing to a comprehensive discussion of green resource usage, the role of digital technologies, and their impact on firm performance, focusing on the Malaysian automotive industry. Each chapter is cohesive in its narrative to address the research objectives.

Chapter 1 discusses an overview of green resources' usage, the role of digital technologies, and firm performance. The chapter begins with the introduction, study background, Malaysian automotive industry history, and current state of the Malaysian automotive sector, emphasising its relevance as a focal point for green practices and technological innovation. The chapter also articulates the problem statement in identifying the gaps in existing knowledge and justifying the need for the research. It defines the research questions and research objectives to guide the study. Additionally, the significance of the study was emphasised by highlighting its contribution to theory, managerial, scholars, and policymakers. The scope of the study delineates the focus of the research. The chapter concludes by providing an overview of the chapter layout and a conclusion on its key elements.

Chapter 2 explores the underpinning theory and the literature review examining the existing studies on green resources, digital technology capabilities, and firm performance. The operational definitions are outlined, ensuring precise interpretations of the terms and constructs used in the study. It also critically reviews past studies to identify field trends, gaps, and debates. The chapter introduces underpinning theories, the Resource Based View (RBV) and Dynamic Capability View (DCV), in which the research is examined. The chapter also develops a conceptual framework that describes the relationships among the key variables, providing a roadmap for the research. The chapter is essential for contextualising the preliminary information within the broader academic perspective.

Chapter 3 outlines the research methodology employed to achieve the research objectives. This chapter entailed a discussion of the research design, explaining the quantitative approach and justification. The population and sampling technique are described, including the criteria for selecting respondents and the sample size. The data collection through a survey discussed the procedures for how the data was gathered. It also discusses the measurement variables, instruments and tools used to measure green resources, digital technology capabilities, and firm performance. This chapter concludes by ensuring the research methodological rigour for reliable and valid findings.

Chapter 4 presents the research findings and discusses them in depth. It provides a comprehensive data analysis using Partial Least Square, Structural Equation Modelling (PLS-SEM) methods to examine the relationships between green resource usage, digital technology capabilities, and firm performance. For clarity, the findings are presented descriptively and inferentially supported with the relevant tables, charts, and diagrams. This chapter includes a discussion of the insights obtained from the data in verifying the research objectives and questions. It demonstrated the significant relationship that contributes to an in-depth understanding of the relationship between the variables within the context of the Malaysian automotive industry.

Chapter 5 concludes the study by summarising the findings and their implications. It provides a synthesis of the results demonstrating how the research addresses the problem statement and achieves the research objectives. The chapter discusses the theoretical and practical implications of the findings, which offered valuable insights for academics, industry practitioners, and policymakers. Finally, the chapter presents a limitation and recommendations for future research. The information identified areas that need further exploration to expand the study's findings. The conclusion emphasises its contributions and paved the way for ongoing discussion into greener achieving sustainability and technology-driven practices in the Malaysian automotive sector. This study provides holistic insights and contributions to the field of sustainability, digital technology, and firm performance.

1.10 Chapter Summary

This chapter has laid out the background of the research and identified the importance of green resource usage and the role of digital technology capabilities in enhancing firm performance in Malaysia automotive manufacturing firms, encompassing both vehicle assemblers and the parts suppliers. The problem statement and the research gaps framed established the research questions and objectives that focus on the investigation. This chapter also emphasises the significance of the research, with practical implications specifically targeted to automotive manufacturing firms and the scope of the study, which examines the impact of green resources and the role of digital technology capability on firm performance among Malaysian automotive industry firms. Additionally, the chapter layout provided a roadmap for this study and groundwork for the following discussions and analyses in the subsequent chapters.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter presents the underlying theories for green resources and digital technology capabilities to achieve competitiveness and boost automotive firm performance. The motivation for this study relies on the relationship between using green resources and firm performance, the relationship of digital technology capabilities on firm performance, and the integration of both on firm performance. Grounded in the Resource-Based View (RBV) and Dynamic Capabilities View (DCV), past studies have been critically reviewed to identify research gaps. A conceptual framework is developed, and the hypotheses are formulated to examine the direct and mediated relationship among green resources, digital capabilities, and automotive firm performance.

2.1 Underpinning Theory

The underpinning theories used in the study are the Resource-Based View (RBV) and the Dynamic Capabilities View (DCV). The application of these theories is discussed below.

2.1.1 Resource-Based View (RBV)

The Resource-based View (RBV) serves as a foundational framework for understanding how firms perform and sustain competitive advantages through the strategic use of their internal resources. RBV identifies valuable, rare, inimitable, and non-substitutable (VRIN) resources and is crucial for achieving sustainable competitive advantage (Alos-Simo et al., 2020; Barney et al., 2001; Hart, 1995). The view stressed the importance of leveraging a firm's internal strengths and capabilities in maintaining resilience and adaptability in dynamic market environments. Hart (1995) argued that when coupled with these distinctive internal resources, firms' capabilities enhance competitive edges that focus on short-term strategies and long-term strategic positioning to improve firm performance. Firms must actively utilise their resources to capitalise on their core competencies to remain internally resilient and have the ability to respond to opportunities and threats in the external environment. The RBV elucidates the connections between a firm's resources, competitive advantages, and performance. Firms possessing these resource characteristics can develop their capabilities and exploit their competitive advantage to boost performance, as illustrated in Figure 2.1.

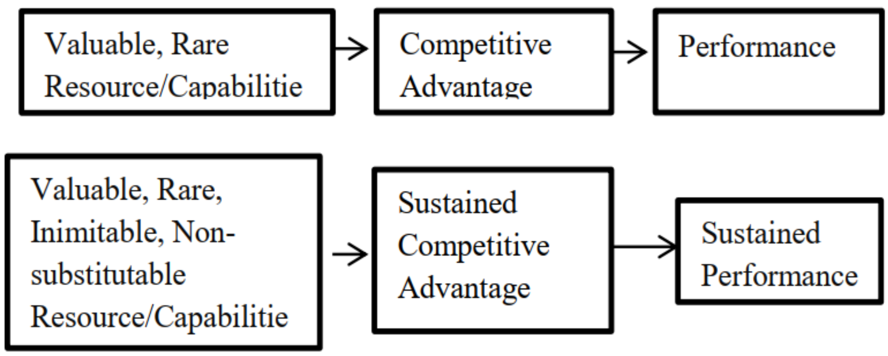


Figure 2.1: The Resource-Based View (RBV)

Resource: Newbert (2007)

According to Barney (1991), resources should be unique and rare so that they cannot be easily imitated or substituted by competitors. They constitute a key factor for an organisation to utilise and implement strategies to achieve a sustainable competitive advantage. Furthermore, firms must possess heterogeneous resources that may not be strategically mobile across organisations, meaning the resources cannot be transferable or replicated, further strengthening the firm's competitive position. Firms with valuable resources can identify and implement strategies to enhance the firm's efficiency and effectiveness in achieving sustainable performance outcomes.

The RBV also establishes a direct relationship between a firm's resources, competitive advantage, and performance. Barney et al. (2001) expanded on this and elucidated that resources are inherently static and will evolve due to external changes such as technological advancements, market dynamics, and industry trends. As such, the resources that represent VRIN allow organisations to develop innovative strategies that enhance performance by identifying internal strengths, responding to external opportunities, and addressing internal weaknesses to neutralise external threats. This strategic orientation fosters a proactive competitive approach where firms adapt to environmental changes while maintaining their competitive advantage to improve organisational performance. Accordingly, the firms' utilisation and deployment of resources are important in determining their long-term competitiveness and performance. This dynamic aspect of the RBV highlights the need for firms to continuously innovate and refine their resources to maintain their relevance and edge in rapidly changing business environments.

2.1.2 Dynamic Capabilities View (DCV)

The Resource-Based View (RBV) provides a valuable foundation for understanding how firms achieve competitive advantage through valuable, rare, inimitable, and non-substitutable organisational capabilities resources. However, how firms renew and adapt their resource base in dynamic circumstances is still unclear. The resources and capabilities contributing to a firm's competitive advantage have limited life spans due to market changes (Hart & Dowell, 2011). This limitation of the RBV highlights the necessity for a complementary perspective that focuses on adaptability and resource renewal, particularly in volatile and dynamic contexts. In pursuit of competitive advantage, the Dynamic Capabilities View (DCV) addresses this gap by focusing on a firm's ability to integrate, build, and reconfigure the internal resources effectively in response to a rapidly changing environment (Teece et al., 1997).

The dynamic capability view (DCV) enhances the RBV by elucidating the shift of the firm's focus from static resource possession to the organisational processes that enable the firm to sense opportunities and threats, seize opportunities, transform, learn, integrate, and reconfigure resources. These adaptive processes enable firms to sustain competitive advantage in dynamic environments, fostering core competence through recognising market trends, leveraging technology, and adjusting resources that motivate firms to innovate and continuously evolve their products to maintain relevance and sustainability in the market (Teece, 2014). These processes drive firms to innovate, adapt, and evolve their products to remain relevant and competitive in the market.

Furthermore, this view also underscores the idea that sustainable competitiveness is no longer derived from possessing valuable resources but from a firm's ability to proactively renew and align its resources.

In addition, Teece (2018) emphasises the critical role of managerial capabilities in configuring and executing dynamic capabilities. The strategic and tactical management levels are pivotal in fostering innovation, designing strategies, and effectively orchestrating resources to face external changes. Managerial acumen is essential for recognising new opportunities, mitigating risks, and enabling firms to thrive in an evolving environment. Pavlou and Sawy (2011) concurred that technology capabilities serve as key enablers of dynamic capabilities, allowing firms to sense, learn, integrate, and coordinate internally as proposed in Figure 2.2.

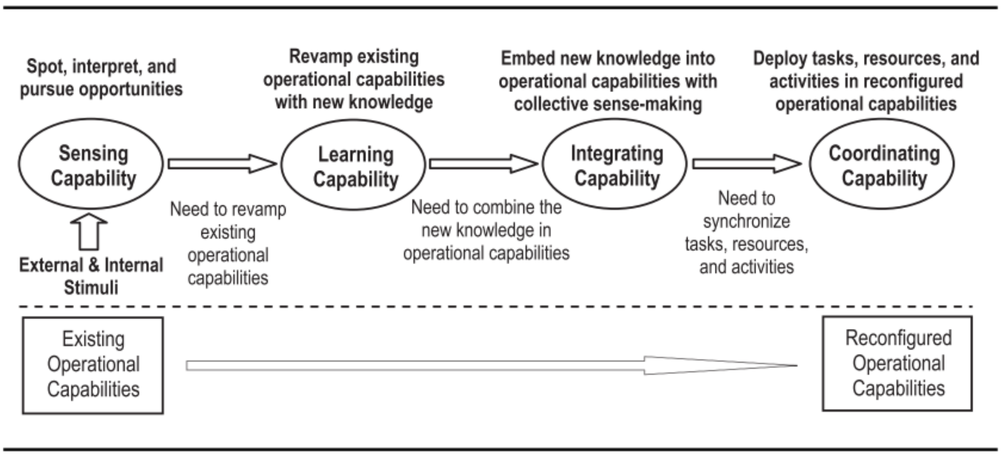


Figure 2.2: Dynamic Capability View

Resource: Pavlou and Sawy (2011)

The digital technology capabilities encompass the following components:

i) Sensing capability - As Teece et al. (1997) noted, this is acquired to adapt and respond to dynamic changes, scanning the environment to seek opportunities and reconfigure ahead of competitors. Hence, the activities pertain to frequent scanning of opportunities in utilising digital technology to optimise green resource usage, identify customer needs, and respond to market trends and requirements in exploring new opportunities.

ii) Learning capability – Organisations must acquire knowledge to find solutions and create new knowledge and skills to reconfigure existing operations. Thus, learning capability serves to enhance existing operational capabilities with new knowledge and skills to augment dynamic capabilities within the organisation.

iii) Integrating capability – This refers to the organisation's ability to combine internal resources to enhance existing operational capabilities. Individuals possess most of the new knowledge shared through learning, which must be integrated at a collective level.

iv) Coordinating capability – This capability necessitates the appropriate allocation of personnel to tasks to ensure better synchronisation of tasks and activities horizontally and vertically within the organisation. The organisation's ability to coordinate and implement tasks, resources, and activities is an integral part of the new operational capabilities.

By leveraging technology, firms can improve their agility and responsiveness, ensuring sustained performance and competitive advantage in the dynamic market.

2.1.3 RBV, DCV, and Relevancy

According to the RBV, a firm that focuses on internal resources and core competencies that it already possesses can sustain its performance and achieve a competitive advantage. In the context of ongoing transformation in the automotive industry, it is important to utilise its internal resources in achieving operational and environmental benefits (Azman & Ahmad, 2023). Sakrabani et al. (2020) classified resources into tangible, intangible and people-based resources, noting that each plays an important role in enhancing firm performance. In this study, green resources are defined to include tangible and people-based resources such as renewable resources, reusable parts, and recyclable waste, conserving energy and water, the adoption of green technologies, and skilled and experienced workers engaged in resource efficiency and the development of sustainable products and processes. While digital technologies are also considered a tangible resource, the effective integration with green practices across organisations' processes depends on knowledge, learning, and expertise (Barney, 1991). These attributes are classified as intangible resources.

Over the years, RBV has been criticised for firms focusing on existing resources, placing less emphasis on dynamic changes and ignoring how resources evolve over time (Hart & Dowell, 2011). The RBV relies on the two core assumptions of heterogeneity and immobility that lead firms to improve their performance in achieving competitive advantage (Bag et al., 2021). As such, if firms possess unique resources can perform better than their competitors and pursue different strategies to strengthen the processes and improve performance. This is because heterogeneous resources will encourage firms to adopt innovation to develop new products. Moreover, valuable resources are immobile and difficult for rivals to imitate. This raises barriers for competitors to replicate the firm's success, and as such, it creates value that is reflected in financial and operational performance. Thus, green resources and digital technology are identified as a potential source of competitive advantage under the RBV (Barney, 1991), where these static resources are transformed into dynamic performance outcomes. However, the RBV is widely debated (Pertusa-Ortega et al., 2010). Moreover, critics have highlighted the absence of an institutional role (Patnaik et al., 2022). Despite that, three critical limitations motivate integrating with the dynamic capabilities view (DCV). First, RBV's static assumption inadequately explains how the automotive industry renews its green resources and optimises the digital technologies in dynamic environments (Hart & Dowell, 2011). Second, RBV passively assumes that green resources automatically confer an advantage on the automotive industry without specifying the mechanism of transformation. Lastly, the lifespan of green resources and digital technologies will erode as markets evolve, which pushes the automotive industry to develop renewal capabilities.

Thus, the automotive industry must select and combine green resources with quality digital technologies that possess the VRIN framework to sustain performance in achieving competitive advantage. To enhance the resource efficiency, the DCV further explains how firms gained and sustained competitive advantage during the complex, uncertain, and volatile market (Bag et al., 2020). This study will provide a better understanding that competitive advantage is not gained through possession of scarce resources but through the organisation's capability to develop, deploy, and enhance them effectively. It is the firm's capabilities that are shaped by individual skills and organisational structures and processes. Moreover, while resources can be imitable due to patents, property rights, and knowledge barriers. As such, competitors may still struggle to imitate due to information asymmetries. Thus, firms must actively integrate, build, and configure the resources to acquire competitive value that helps to achieve sustained performance (Newbert, 2007; Teece et al., 1997).

This study proposed an explicit conceptual bridge, where RBV identified green resources and digital technologies as valuable, rare, inimitable, non-substitutable, and organisation-specific. Past study of Tsou and Kim (2025) proved that automotive firms that demonstrate VRIN and high-quality resources are positioned better compared to firms that adopt standard and baseline resources to sustain. The firms' adopted standard and baseline resources are still struggling and scaling up to achieve a sustained performance. On the other hand, DCV specifies how these green resources are activated and enhanced by integrating with digital technologies. The internal dynamic capabilities are built and enhanced through sensing, learning, integrating, and coordinating to produce performance outcomes that would otherwise remain undeveloped. Khan et al. (2026) demonstrated that green resources are "latent" without innovation capability and technology adoption. The study showed that resource possession is not sufficient alone to explain the environmental performance, but the inclusion of digital spurring increases explanatory power. Similarly, Kankanamge et al. (2026) found that digital transformation was a significant mechanism through which digital resources yield green operational performance, with direct effects not significant without the transformation capabilities.

To enhance the DCV effectiveness, Pavlou and Sawy (2011) identified four higher-order dynamic capability components to develop and deploy the green resources by integrating digital technology effectively in the automotive industry:

i) Sensing capability enables the automotive industry to scan the environment to identify opportunities and threats by using digital technologies tools to detect resource inefficiencies, regulatory shifts, and market demands for green products.
ii) Learning capability requires the automotive industry to acquire knowledge to create solutions and reconfigure operations by building organisational competence through combining digital technologies with green materials.
iii) Integrating capability able to enhance firm performance by embedding digital platforms into circular production systems, such as remanufacturing, recycling, and waste tracking.
iv) Coordinating capability enables the automotive industry to allocate personnel and synchronize tasks aligned with production, logistics, and sustainability divisions through digital technology.

Thus, RBV and DCV are more suitable and relevant in the context of this study. As such, the green resources that reflect the VRIN are important in interacting with high-quality digital technologies to enhance the firm's internal capability to be more dynamic. In this digital era, digital technology acts as an enabler. Integrating green resources with effective digital technologies enables the automotive industry to renew and shape the firm's strategic response across divisions towards the changing demand and environments. Figure 2.3 visualises the conceptual bridging.

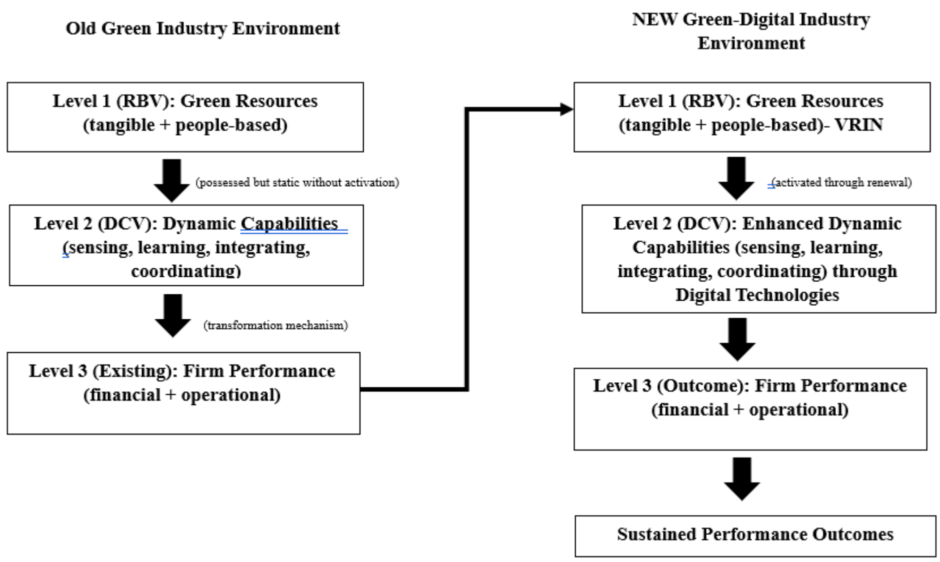


Figure 2.3: Proposed Green-Digital Framework based on RBV-DVC

Source: Develop for Research

In the traditional green industry, green resources are identified as potential resources that possess VRIN. However, the resources remain static without activation, which demonstrates the firms with the existing rather than sustained performance outcome. In contrast, the new green-digital industry introduced DCV as the missing transformation mechanism. Through dynamic capabilities dimensions of sensing, learning, integrating, and coordinating, activate and renew the green resources. This activation directly addresses the RBV's static assumption. Moreover, the digital technologies enhance these dynamic capabilities. The automotive firms will be able to respond to market changes and extend the competitive lifespan of these green resource bundles. Consequently, RBV explained what resources are required, DCV explained how these resources are transformed, and digital technologies amplify the effectiveness of this transformation, which led to sustained performance outcomes.

Thus, RBV and DCV have been extensively applied to explore sustainability, green practice, circular economy, digital technologies, and transformation (Alos-Simo et al., 2020; Bag et al., 2021; El-Kassar & Singh, 2019; Gupta et al., 2020; Li et al., 2022; Matarazzo et al., 2021; Okorie et al., 2023; Schmidt & Scaringella, 2020). In the Malaysian automotive industry context, firms that pursue sustainability and move towards net-zero emissions and a circular economy approach push to utilise green resources to enhance the firm's performance and achieve a competitive advantage. Automotive firms that utilise green resources possess uniqueness through heterogeneity and immobility that represent the characteristics of VRIN. The utilisation of its green resources reflects the automotive firm's commitment to adopting renewable energy, recyclable materials, remanufacturing capabilities, and skilled green process expertise to reduce carbon emissions and improve economic benefits. By integrating green resources with digital technology, firms can innovate new products and improve production efficiencies. Given the complex and firm-specific nature of combining these resources, it is difficult for competitors to imitate. Consequently, the value created from the strategic relationship is expected to improve financial and operational performance within the automotive industry.

In addition, the integration of digital technology capabilities can amplify the efficiency of green resources to further improve firm performance. Due to Industry Revolution 4.0 (IR 4.0), automotive firms adopted digital technologies, such as, Big Data Analytics (BDA), Artificial Intelligence (AI), Augmented Reality, Additive Manufacturing, System Integration, Autonomous Robot, Advanced Material, Cloud Computing, Cyber-Physical Systems (CPS), and the Internet of Things (IoT) (MITI, 2020). The automotive industry organisations leverage these digital technology capabilities to enhance the efficiency of green resources by transforming linear production to circular production systems. This transition supports resource optimisation, waste reduction, and greater environmental sustainability. By effectively sensing opportunities through digital technologies, firms will be better equipped to monitor resource flows, predict demand, and innovate products and processes.

However, the lack of awareness of the circular economy adoption (Yahaya et al., 2024), the lack of expertise for remanufacturing (Raziff et al., 2024), and lagging behind Thailand and Indonesia in end-of-life vehicle (ELV) recycling policies (Jamaluddin et al., 2022) will represent a theoretical boundary. This suggests that RBV's characteristic "resource immobility" assumption may be partially violated when regulatory frameworks are delayed and immature. Thus, the comprehensive dimensions of Pavlou et al. (2011) represent the pool of capabilities that interact and configure the firm's green resources, which are important to address the firm's environmental changes. This study proposes that digital capability serves as a mediating mechanism, theoretically consistent with past empirical studies by Setiawan et al. (2025) and Bindeeba et al. (2025) that positioned a specific mediation pathway enabling green resources to be dynamically reconfigured to enhance firm performance. Drawing on the RBV and DCV perspectives, these capabilities are required to enable Malaysian automotive industry firms to use green resources more efficiently, strengthen competitiveness, and improve finance and operational performance.

2.2 Past Empirical Reviews

Past empirical studies regarding firm performance, green resources usage and digital technology capabilities are discussed below.

2.2.1 Firm Performance

To achieve a competitive advantage, the resilience of internal capabilities will reflect the extent to which the firm can perform more effectively internally than its competitors (Savastano et al., 2022). The organisational strategy articulates a key role in efficiently utilising resources, minimising costs, and leveraging revenues. The core competencies can enhance firm performance by reducing costs and increasing revenues. Measuring revenue in terms of sales growth, profit growth, market share, market value, return on investment, and market penetration rate is often used to measure the efficacy of organisational strategies in enhancing firm performance (Latifi et al., 2021).

Concurrently, past studies categorised a firm's performance into financial and operational performance (Khan et al., 2022; Latifi et al., 2021; Yu et al., 2022). According to Mai et al. (2026), financial and operational performance are important to reflects the internal efficiency and the effectiveness of sustainability implementation in achieving sustained firm performance. The financial performance represents accounting metrics that reflect the firm's profitability. On the other hand, business performance measures market-related measures such as market share, sales growth, market value, and penetration value. The operational outcome encompasses cost reduction and improvements in product quality and market share. Although past studies argued that financial performance measures the real firm's success (Sakrabani and Teoh, 2021) firm performance must reflect the objective and subjective performance of the firm in optimising resource efficiency (Khan et al., 2022). Numerous studies on firm performance employed similar measures to assess the extent of firm performance. However, no single measurement is universally accepted as ideal, and the chosen measurement must align with the firm's objectives to maximise profitability and minimise costs.

Varela et al. (2019) further elucidate that the economic dimension of a firm is measured through profit, turnover, market share, and operational cost. The study elaborates that practising lean manufacturing can increase the firm's profit, turnover, and market share, decrease operational costs, and enhance process performance. Similarly, empirical studies on 147 Malaysian and Chinese automotive firms using covariance-based structural equation modelling revealed that remanufacturing and recycling practices positively impact firm performance (Yu et al., 2022). Another study concurred that automotive firms positively affect firm performance. Sustainable manufacturing processes with ISO 14001-certified firms across various Malaysian industries have demonstrated a significant cost reduction, product quality improvement, and delivery performance (Abdul-Rashid et al., 2017). These manufacturing companies incorporate green initiatives in the manufacturing process to control wastage, reduce the use of excessive resources, and limit energy consumption.

Additionally, global environmental issues and external pressure on sustainability necessitate firms to invest expeditiously in more sustainable approaches in the early 2000s in the manufacturing process to derive economic and operational benefits. Thus, utilising the firm's resources with dynamic capabilities positively impacts sustainability and eco-innovation. A study in Spain across five sectors revealed that eco-innovation positively contributes to firm performance, expressed through sales revenue growth in new and existing (Alos-Simo et al., 2020).

Similarly, green manufacturing can potentially improve the firm's economic performance by reducing waste and business costs. Moreover, adopting these strategies can enhance the firm's performance and achieve a competitive advantage. However, the empirical findings from Turkish manufacturing firms elucidated that green manufacturing adoption has no direct effect on firm performance, likely due to the early stages of green initiatives implementation (Nureen et al., 2023). On the other hand, green practices can increase a firm's turnover in the short term; however, the impact on long-term financial performance requires further investigation. Research on green practices among automotive companies from 22 countries using structural equation modelling indicates that implementing such practices positively influences operational performance but shows a limited direct impact on financial performance (Szász et al., 2021). This demonstrates that the automotive industry gained operational performance more than financial performance. The findings will have direct implications for the integration of green resources with digital capabilities, which may underestimate financial effects if firms are in the early stages.

Empirical research on extant studies pertaining to new-generation technologies has been extensively conducted in relation to firm performance. Bag et al. (2020) found that Industrial Revolution 4.0 (IR 4.0) technology capabilities positively impact firm performance in South African manufacturing firms by enhancing logistics capabilities, resource efficiency, and supply chain operations. The adoption of digital technologies enhances a firm's capacity to utilise resources more efficiently, thereby improving the quality and speed of supply chain operations and delivery. Similarly, a study in Malaysia among retailers revealed that the adoption of Industrial Revolution 4.0 had a positive effect on firm performance (Sakrabani and Teoh, 2020). Furthermore, a study on the effects of IR4.0 technologies among industrial factories in Turkey also demonstrated a positive impact on organisational performance (Calış Duman and Akdemir, 2021). These studies acknowledged that adopting IR 4.0 added value and enhanced the role of internal capabilities in leveraging firm performance and conferring a competitive advantage. It supports the notion that digital technologies function as enablers, assisting firms in increasing profit and production speed and enhancing efficiency while decreasing costs. Digital technologies also facilitate the improvement of firms' sustainability through resource optimisation. Consequently, digital technologies are crucial for firms to enhance process efficiency and profitability. In addition, Martínez-Caro et al. (2020) demonstrated that internally adapted, modified, and reconfigured digital technologies contribute significantly to profitability and competitiveness by optimising resources and creating additional value.

In conclusion, in this study, firm performance can be represented by a dual outcome comprising financial and operational measures. Financial measures are characterised by profitability, revenue growth, market share, and sales growth, while operational measures include cost reduction, quality improvement, production efficiency, and production speed.

2.2.2 Green Resource

Green manufacturing and sustainability strategies have been extensively researched in recent years. The process of production typically commences with the utilisation of resources. Resource efficiency or optimisation is crucial for ensuring a firm achieves its economic and operational outcomes. Using green resources in production minimises environmental impact and achieves resource efficiency (Ng et al., 2017). The use of green resources and industrial emissions is optimised to reflect the company's green manufacturing assessment. To achieve a sustainable green manufacturing process, automotive firms need to emphasise resource efficiency, management control, and product quality at earlier stages, which would enhance the productivity and performance of the automotive industry (Habidin et al., 2018). Environmental management practices embedded in organisations utilise resources efficiently and foster cleaner production to enhance environmental efficiency. It is generally accepted that production transformation begins with the use of resources to create a product.

Consequently, implementing sustainable practices incorporated along the production line commences with utilising green resources. Resources in manufacturing generally refer to renewable and non-renewable resources. Varela et al. (2019) describe using non-renewable and renewable energy and reusing, recycling, and remanufacturing waste material. Concurrently, Wen Chiet et al. (2019) also describe green waste as renewable resources, such as water usage, energy and materials. As such, it can be inferred that renewable resources consist of water, energy and reused waste material, while non-renewable resources consist of non-renewable energy and materials consumed during production. Numerous past studies have discussed the efficient utilisation of resources (Dubey and Bag, 2017; Valase and Raut, 2019) to control emissions and prevent pollution (Abdul-Rashid et al., 2017; Chiet et al., 2019; Varela et al., 2019).

Furthermore, the adoption and implementation of green initiatives describe the environmental and economic outcomes of the firm's performance. Efficient and cleaner usage of resources enables firms to minimise carbon (CO_2) emissions, achieve energy saving, pollution prevention, recycle waste material and use cleaner technology, which ultimately contributes to firm performance (Abdul-Rashid et al., 2017; Alos-Simo et al., 2020). Abdul-Rashid et al. (2017) study on Malaysian manufacturers found that sustainable manufacturing practices significantly reduce costs and improve product quality and delivery performance. On the other hand, Alos-Simo et al. (2020), analysing Spanish firms using the PLS-SEM approach, found that eco-innovation positively contributes to firm performance through sales revenue growth. Moving away from the traditional manufacturing approach to a circular approach is another evolution of green practices. Most manufacturing industries, particularly the automotive industry, integrate these practices into their operations, creating a more resilient and sustainable business model. According to Yu et al. (2022), using the CB-SEM approach on 147 Malaysian and Chinese automotive firms, found that remanufacturing and recycling practices positively influence firm performance. Moreover, a study in Indonesia automotive industry by Setiawan et al. (2025) found that green innovation positively affects business performance.

Additionally, in Malaysia, a study by Habidin et al. (2018) among Proton vendors on implementing sustainable manufacturing practices revealed that manufacturing processes and environmental management are among the critical factors contributing to the success of sustainable practice. Hence, utilising green resources with internal capabilities can enhance production scale and quality. It is indisputable that manufacturing processes are the primary contributors to CO2 emissions, pollution, waste, excessive energy utilisation, and the use of hazardous materials. Ultimately, achieving sustainable development in green manufacturing aims to control and reduce the consumption of green resources because the manufacturing process consumes various types of resources that release negative externalities to nature (Valase and Raut, 2019).

Hence, green resources positively affect environmental performance or efficiency (Abdullah et al., 2017). The performance or efficiency of the environment is interchangeably used for reducing emissions, waste, resources, harmful materials, energy consumption, and environmental hazards and increasing recycling and environmental technology. Prominent automotive manufacturers such as Toyota Motor Corporation, General Motors Corporation, and Volkswagen Group have demonstrated that utilising green resources aligns with the firm's green operation initiatives in manufacturing, which enhances environmental and firm performance (Nunes and Bennett, 2010). The comparative analysis elucidated that these major automotive producers had adopted various sustainability strategies to mitigate environmental adverse effects. These initiatives contributed to the reduction of carbon emissions in the production process. Utilising cleaner fuel, implementing more environmentally friendly plants, and adopting green technologies for the production process with designed remanufacturing may sustainably enhance the firm's performance.

Past studies elucidate that most industries have adopted green practices, which are important for achieving sustainability and firm performance. Nothing that the organisation's internal resources and core competencies are important to benefit economically. A systematic review study of Giampieri et al. (2019) revealed that the automotive production process encompasses various stages and involves a heating process that may increase excessive energy usage; as such, the utilisation of green technology positively enhanced economic and environmental outcomes. Similarly, eco-innovation comprises technical eco-innovation, which necessitates the adoption of technologies in the production process to enhance environmental performance (Mat Dahan et al., 2017). Such activities contribute to the reduction of operational costs. Additionally, according to Buruzs and Torma (2018), eco-innovation capabilities can reduce the consumption of non-renewable resources, materials, waste, and harmful substances.

Past studies concurred that industrial processes must adopt environmental initiatives with eco-innovation to benefit economically and environmentally. For instance, the Toyota Corporation implemented green process innovation in production, such as adopting waterborne paint in the vehicle painting process to reduce chemical substance emissions (Ng et al., 2017). The utilisation of natural resources promotes cleaner production (Vaz et al., 2017), as renewable energy sources such as biofuel or biodiesel, the reuse of car bodies in the manufacturing process, the implementation of hybrid petrol-electric power vehicles, fuel cells, disassembly, dismantling, and recycling constitute resource efficiency activities.

Due to excessive consumption of natural resources and harmful components such as base and critical metals, reuse, recovery and recycling are encouraged for environmental and economic reasons (Aguilar Esteva et al., 2021). The utilisation of waste and recycled resources in the automotive industry should commence at the product design stage to control and optimise their usage without compromising vehicle safety. Firms should plan and measure resource usage to identify appropriate waste management methods (Shahbazi et al., 2018). Using waste resources contributes to economic savings and sustainable environmental outcomes (Buruzs and Torma, 2018; Mat Dahan et al., 2017). Accordingly, firms should be equipped with suitable technology to test, plan, control, and monitor resource efficiency.

Contrarily, an empirical study in Spain among 300 manufacturing sectors using ordered logit regressions found that eco-innovation positively influences economic performance but has no significant effect on environmental performance, however, the life cycle assessments, recycling and remanufacturing positively influence economic and environmental performance (Bellantuono et al., 2021). Although green innovation adoption influences firm performance, it may not be sufficient for firms to reap the benefits in the long term if they fail to build and enhance the capabilities to embrace the circular economy. Nureen et al. (2023) concurred that the green manufacturing approach at Turkish firms had no direct effect on firm performance, attributing it to its early stage implementation. The findings agreed that any green initiatives required a minimum of three to five years to materialise financially.

On the other hand, Szasz et al. (2021), found that green practices improved operational performance, but had a limited impact on financial performance, which may be due to regulatory restrictions. This means operational performance sustains immediately, however financial performance can only be sustained after the regulatory or market conditions are fulfilled. Nonetheless, a study conducted by El-Kassar & Singh (2019) in the MENA region demonstrated that green product innovation influences environmental performance, but there is no significant effect on organisational performance. The finding is important as defending that green innovation alone does not confirm the organisational performance and suggests that a missing mechanism is needed to sustain competitiveness.

In parallel with this, the practising circular economy components exhibit limited readiness to incorporate, mostly in their nascent stages. Correspondingly, a bibliometric analysis by Kifor et al. (2023) found that most of the firms in the automotive industry still practice the traditional approach and lack practice toward a circular economy, which could be why resource efficiency cannot be maximised. An empirical finding using multiple regression analysis demonstrated that high-tech technology firms in Kedah, Malaysia, consume excessive energy, adopt lower recycling practices, and rely on harmful material usage, potentially negatively impacting the environment (Abdullah et al., 2017). Consequently, environmental efficiency is less significant in terms of environmental sustainability practices. Additionally, a comprehensive review by Nazir and Shavarebi (2019) revealed that environmental issues remain neglected in the Malaysian automotive sector and concluded that re-manufacturing would be the most effective approach to address resource constraints and pollution prevention issues.

Moreover, Thailand and Indonesia, among the major automotive producers, have advanced EV production and policy frameworks compared to Malaysia. A comparative study among Southeast countries, adopting the qualitative method using various secondary sources, suggests that Malaysian firms must adopt and implement maximum recovery and recycling (Jamaluddin et al., 2022). Although Malaysia is emerging, it is less mature compared to Indonesia and Thailand (Kifor & Grigore, 2023). Conversely, the benefit of a circular economy only flows with the coordination and integration of high-impact strategies on sustainability by the internal stakeholders in managing resource efficiency. The benefits may not be fully fulfilled due to quality, safety, and cost limitations, especially when recycling or reusing materials (Aguilar Esteva et al., 2021) and lack of expertise, technology capacity, learning process, and resistance to change at the managerial level (Yahaya et al., 2024). A case study using the Dematel method among 10 Indian automotive firms that have implemented green manufacturing for an average of 10 years or more revealed that a lack of management skills, necessary tools, and training on sensitive environmental processes hindered and slowed the penetration of green manufacturing in India (Pathak et al., 2021). Additionally, Raziff et al. (2024), an exploratory study in the automotive industry in Malaysia, revealed that remanufacturing automotive components requires more expertise with adequate knowledge and know-how to manage resources efficiently, which could positively impact firm performance. These studies elaborate on the importance of internal core competencies, particularly leveraging people skills and technology in manufacturing processes to integrate and manage internal resources efficiently.

Enhancing internal capabilities with skills focusing on green-centric initiatives is important to improve the manufacturing process in pursuit of sustainability value (Ogbeibu et al., 2020). A survey conducted among manufacturing firms in India revealed that management focus on green-related components, such as waste material, inventory, labour turnover, and technological factors, including skills or expertise, had improved sustainability practices performance and minimised environmental impact (Valase and Raut, 2019). Therefore, managerial support will contribute to environmental initiatives (Sakrabani and Teoh, 2020; Savastano et al., 2022). Such initiatives may prove challenging to implement if the organisation is excessively complex, affecting the culture, and senior management's lack of engagement may lead to implementation failure. Thus, the distinction between operational and financial performance explains the contradictions. Green resources consistently improve operational efficiency but reap the financial returns when markets reward green differentiation or regulation internalises the environmental costs. In emerging markets like Malaysia, green practices remain uncertain; operational performance is the more immediate and reliable sustained outcome (Jamaluddin et al., 2022). As such, financial performance may lagged and reap after the operational gains depending on market and regulatory conditions. Organisations that utilise and renew green resources can achieve a competitive advantage and reduce production costs through sustained performance. Employing rare, valuable, inimitable, and non-substitutable green resources can enhance their capability to achieve firm performance and maintain competitiveness (Munodawafa and Johl, 2019). The uniqueness of these resources enables firms to develop and enhance their capabilities, enhancing material efficiency and positively influencing firm performance.

2.2.3 Digital Technology Capabilities

The preceding industrial revolution focused on market changes and process enhancement for manufacturing development and achieving sustainability. However, the current industrial revolution 4.0 (IR 4.0) primarily interconnects the firm's capabilities to utilise resources efficiently to enhance performance. Digital technologies encompass a set of smart technologies, particularly Big Data, the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Cloud

Computing, to transform traditional manufacturing into a digitalised manufacturing process (Hamdi et al., 2019; Li et al., 2020). Digital technologies function as dynamic capabilities to create, renovate, and transmit the firm's resources, enhancing its competitiveness (El-Kassar and Singh, 2019). Regarding these industrial revolution 4.0 enablers, Varela et al. (2019) elucidated that these technologies could stimulate economic performance. The advantages gained include increased profitability, value, efficiency, competitiveness, turnover, market share, decreased operational cost, and increased unambiguous renewable resources and production processes.

Numerous past empirical studies revealed that digital technologies positively influence firm performance. These studies demonstrated that Cloud-based Enterprise Resource Planning (ERP) capabilities, the role of big data, the adoption of IR 4.0 technologies, and IoT capabilities influenced firm performance (Bag et al., 2020; El-Kassar and Singh, 2019; Gupta et al., 2020; Li et al., 2020; Singh and El-Kassar, 2019). Bag et al. (2020) studied South African automotive component manufacturers and found that Industry 4.0 capabilities positively impact firm performance through enhanced logistics and resource efficiency. Additionally, a study on Turkish industrial factories implies that IR4.0 technologies positively impacted the organisational performance (Calış Duman & Akdemir, 2021).

Similarly, a study on 147 Malaysian retailers found that the IR 4.0 adoption positively affected the firm's performance across all the Balanced Scorecard dimensions (Sakrabani & Teoh, 2020). Moreover, Senadjki et al. (2023) studied

164 Malaysian firms using the PLS-SEM method and found that digital transformation positively influences firms' financial performance. In the same way, implementing internal digital technology capabilities enables firms to improve dynamic production and achieve a competitive advantage in the long term. Scholars extensively discuss integrating internal capabilities among organisations, technology, and humans. The relevant past studies provided insight into the contribution of digital technology capabilities to the firm's outcome. The role of such technologies exhibited the integration of resources used in the production chain to accelerate firm performance. Firms could perform better in terms of delivery time, flexibility, enhanced production quality, and reduced operational cost (Bag et al., 2020, 2021).

Organisational commitment, motivation, skilled personnel, and diffusion of digital technology are essential (Eidhoff et al., 2016; Singh and El-Kassar, 2019) to sustain competitiveness. Previous studies on these digital technologies have elucidated the benefits gained by manufacturing firms through IoT adoption (Syafrudin et al., 2018). The firms are able to enhance the working environment, prevent production errors, and improve decision-making at the management level. Furthermore, digital technology supports production planning by controlling the information process efficiently. Consequently, firms have shaped their IoT, cloud computing and big data and analytics according to their capabilities in order to expedite the firm's production, achieve operational efficiency, and perform robust firm performance (Li et al., 2020). Another study among the Korea Industry 4.0 association members on smart factories and big data revealed that the adoption of big data influences the firms' facility in adopting this technology, wherein the organisation's readiness to support skilled personnel to use resources is important in achieving information efficiency (Jang et al., 2019).

Moreover, the study on IoT capabilities and competitive advantage among Information Technology personnel demonstrates a positive contribution (Dunaway Virginia et al., 2019). Identifying the IoT's ability ultimately delivers phenomena that benefit firm performance. Similarly, Rashidirad and Salimian (2020), in a study using structural equation modelling (SEM), revealed that the dynamic capabilities of sensing, learning, integrating, and coordination directly impact value in Small and Medium Enterprises (SMEs). The study reinforces the findings by supporting the grounded view of dynamic capabilities, which posits that firms must continuously seek and seize new opportunities, learn, integrate, and reconfigure resources to maintain competitiveness and create value. Savastano et al. (2022) finding corroborated the notion that digital manufacturing capabilities positively affect firm performance and partially mediate the positive effect of digital capability on firm performance. The results suggest that firms must evaluate investing in digital capabilities to enhance their processes and performance. If the firm can utilise this technology to sense, learn, integrate, and coordinate resources, it rarely needs to change or struggle to face competitors.

However, a previous study on dynamic capabilities and firm performance among SMEs by Hernandez-Linares et al. (2021) revealed that sensing and coordination capabilities did not significantly influence firm performance, but learning and integrating capabilities significantly influenced firm performance. The finding posited that SMEs that have a strong relationship with their customers may not necessarily require sensing the rare and unique resources to enhance their performance, but the learning and integrating capabilities were crucial to swiftly learn and integrate resources within the firm to improve firm performance. This is in line with a study conducted in China among 165 Chinese manufacturing companies using PROCESS macro analysis, which found digitalisation capabilities had a statistically insignificant direct effect on firm performance but a significant indirect effect through market capitalising agility and operational adjustment agility (Li et al., 2022). This finding strongly implies that building digital capabilities alone is insufficient, as a firm needs to transform these capabilities into agility. Thus, firms must constantly renew and enhance their digital capabilities to remain sustained.

Warner and Wager (2019) propose that a firm must reform internally by acquiring a digital mindset within an organisation to sense and seize opportunities that enable the firm's agility and improve digital maturity. Thus, at the managerial level, sensing and seizing tactically with a well-equipped skill set is necessary to integrate and coordinate resources to enhance internal performance and achieve competitive advantage (Schmidt and Scaringella, 2020). The firm's agility is demonstrated to directly influence digitalisation capabilities and firm performance during uncertainty, such as the COVID-19 outbreak. To address uncertainty, firms leverage digitalisation capability to enhance their agility to improve firm performance and gain competitiveness among manufacturing companies (Li et al., 2022). Hence, firms are encouraged to explore new opportunities to shape and transform their resources to strengthen their dynamic capabilities. This disruptive digital technology can enhance a firm's competitiveness and confer a set of benefits to the firm's economic outcomes.

Despite the contribution of digital capabilities towards the organisational level and the assimilation of digital technology in the production process, firms need to integrate sustainability globally. External pressures such as consumer demand, market demand, and government policies towards green resources adoption, require firms to modify and adapt their internal capabilities to sustainable production. Beier et al (2018) and Belhadi et al. (2020) found that integrating big data capabilities with green resources enables energy efficiency and production improvement. Furthermore, integrating Big Data capabilities with green resources enables firms to achieve energy efficiency and improve production (Singh and El-Kassar, 2019; Syafrudin et al., 2018). Conversely, a prior study found that big data has minimal influence on green innovation (El-Kassar and Singh, 2019). The relevant previous studies have concurred that integration of digital technology and sustainable manufacturing is able to unlock a greater potential of a firm's capabilities in achieving better resource efficiency, energy efficiency, and pollution prevention, and enhance firm performances (Beier et al., 2018; Belhadi et al., 2020; Y. Li et al., 2020; Syafrudin et al., 2018; Varela et al., 2019).

Khan et al. (2022) studied manufacturing firms in Eastern European countries using covariance-based structural equation modelling, indicating that adopting

Industry 4.0 significantly reduces waste from production, enhancing remanufacturing and efficient use of natural resources. Similarly, Yu et al. (2022) study revealed that adopting digital technology positively influences the remanufacturing and recycling process in automotive firms in Malaysia and China. Though knowing that automotive manufacturers are major contributors to carbon emissions, adopting digital technologies enables monitoring and observing resource consumption along the manufacturing processes. It is important to align predictive analytics tools with the processes to drive zero-carbon manufacturing forward, especially in minimising waste in the back-end vehicle manufacturing process (Syed, 2023). Another study conducted in India among 289 manufacturing firms using covariance-based structural equation modelling revealed that tangible, intangible, and human resources skills for Industry 4.0 positively influenced manufacturing firms' carbon neutrality capability (Bag et al., 2024).

More rigorous exploration is needed to integrate green practices, notably emphasising resource consumption efficiency and digital technologies (Belhadi et al., 2020; Li et al., 2020). In the Belhadi et al. (2020) study, green manufacturing practices fully mediate the relationship between Big Data Analytics capabilities and environmental performance. However, bundling green resources and deploying digital technology capabilities into core competencies is important and will make it more difficult for competitors to imitate rather than just adopt digital technology. The capabilities of digital technology may create, transform, and transfer green resources to improve the firm's performance, contingent upon the digital organisational culture (Martínez-

Caro et al., 2020). A study by Setiawan et al. (2025) in the Indonesian automotive sector found that digital technology significantly mediates the relationship between green innovation and business performance, with the direct effect reduced to non-significance after inclusion of the mediator. The findings highlighted that digital technologies play an important role as mediators in translating the green resource efforts into business performance. On the other hand, another study found that technology adoption moderates the relationship between green resources and environmental performance, where green resources are demonstrated as "latent value" without enablers (Khan et al., 2026). These relevant findings strongly justify positioning digital technology capabilities as a mediator, though the direct effect may be significant, but is theoretically expected to be weaker than the indirect effect through mediation.

On the other hand, firms encounter difficulties in implementing green initiatives with digital technologies due to financial constraints (Gupta et al., 2020). Establishing digital technologies within the firm has not been problematic, as most firms are progressing towards the IR 4.0 revolution; however, emerging technologies in the future may surpass the dynamic competitiveness of the business, potentially incurring financial and environmental burdens (Li et al., 2020). Consequently, digital technologies may have unintended negative influences on environmental sustainability. A qualitative study combining systematic literature review with focus group discussions on digital transformation and net-zero manufacturing revealed contradicting findings. Okorie et al. (2023) systematic study revealed that adopting new technologies mainly improves resource efficiency and net zero emissions; however, the insights from focus group discussions reported no association between digital transformation and net zero emissions in their operations. Similarly, a study on manufacturing companies in Malaysia using impact-uncertainty analysis and descriptive analysis revealed that achieving full automation and robotics in Malaysian manufacturing raises concerns about operational benefits due to a shortage of highly skilled workers (Azman and Ahmad, 2023). Similarly, a systematic review revealed that implementing the Internet of Things to support Industry 4.0 in Malaysian manufacturing industries is still in its infancy and lags behind other ASEAN countries, mainly due to high investment costs and a lack of technical knowledge (Adnan et al., 2023).

Leveraging the integration of green resources with digital technology capabilities is promising theoretically, but empirically contingent. The barriers are not merely technological but capabilities-based as the firm's lack of sensing, learning, and coordination capacities to deploy and enhance the digital tools effectively. In conclusion, building and enhancing internal digital technology capabilities are essential for constructing, transforming, and reconfiguring green resources to enhance firm performance and maintain competitive advantage. This directly justified this study’s adoption of RBV and DCV’s four capability dimensions as the mediation mechanism.

2.3 Gap in Literature

Numerous studies on sustainability in manufacturing across various sectors have been conducted, focusing on cleaner production (Giampieri et al., 2019), green practices (Abdul-Rashid et al., 2017; Valase and Raut, 2019), green innovation

(Alos-Simo et al., 2020; El-Kassar and Singh, 2019), and green manufacturing (Chiet et al., 2019; Ng et al., 2017).

Use of sustainable materials (Aguilar Esteva et al., 2021; Varela et al., 2019; Vaz et al., 2017), recycling, remanufacturing, and ELV recovery practices (Mohamad-Ali et al., 2024; Raziff et al., 2024; Yu et al., 2022), energy and water efficiency (Aguilar Esteva et al., 2021), green technology (Setiawan et al., 2025), and technical skills (Yong et al., 2020) are discussed widely to mirror resource efficiency. In this study, green resource usage represents eco-friendly materials, waste and recovery materials, water and energy conservation, green technology, and green technical skills, which serve as independent variables to describe the behaviour of the Malaysian automotive industry in optimising resource efficiency. A similar past study emphasises VRIN resources as the highest operational capabilities in the automotive sector, but green resources are not examined (Tsou & Kim, 2025). Green resources possess valuable, rare, imitable, and non-substitutable characteristics that are identified as a potential source of competitive advantage under the RBV (Barney, 1991). Therefore, there is limited empirical evidence on the effects of green resources in the automotive industry.

Consequently, the RBV predicts a positive effect of green resources on automotive firm performance. However, relevant studies stressed mixed empirical findings (Bellantuono et al., 2021; Nureen et al., 2023; Setiawan et al., 2025; Szász et al., 2021; Yu et al., 2022). The mixed results are due to the firms' internal barriers hindering. Pathak et al. (2021) recognised that the weak integration between internal competencies and resource efficiency influences firm performance. In the same vein, Chiet et al. (2019) concurred that limited knowledge of firms on environmental management, coupled with a lack of expertise (Yahaya et al., 2024), results in green resources not having a significant effect on a firm's performance.

In addition, the financial concerns delayed firms from acquiring the full benefits of the integration of green resources and digital technology in achieving sustained performance (Gohoungodji et al., 2020; Jamaluddin et al., 2022). Although the findings justified that the operational performance can be achieved in the short term, the financial performance can only be sustained after the regulatory or market conditions are fulfilled, upon activation. The relevant past studies describe the existence of resource usage, but how green resources transform into firm performance during the earlier transition is still inadequate, particularly in most of the automotive industry. Hence, this addresses the gap in determining the direct effect of whether green resources positively influence firm performance. The findings will provide insights into the current state of Malaysian automotive industry firms' behaviour on green resources usage.

Although the emergence of net-zero emissions and the circular economy among scholars is ongoing. On the other hand, numerous studies focused on the role of adopting digital technologies in facilitating firm performance and sustainability (Dubey and Bag, 2017; El-Kassar and Singh, 2019; Singh and El-Kassar, 2019; Varela et al., 2019). Ultimately, past studies have shown that digital technologies positively influence firm performance (Bag et al., 2020) and the circular economy (Okorie et al., 2023). Meanwhile, Li et al. (2020) demonstrated that digital technologies had an insignificant direct effect on firm performance. In addition, Setiawan et al. (2025) study adopted digital technologies as a mediator and found that it mediates the relationship between green innovation and firm performance. Kankanamge et al. (2026) found that enhancing firm performance can be achieved when digital technologies act as an enabler, since the direct effects are not significant without transforming its capabilities.

Nevertheless, there is an inconsistency in these findings regarding whether digital capabilities can directly enhance firm performance or require an activation mechanism. The IR 4.0 enablers and digital technologies remain nascent and require further study of their impact on firm performance and resource efficiency (Haleem and Javaid, 2019; Haseeb et al., 2019; Valase and Raut, 2019). There are limited studies on bundling the resources and capabilities, as the past studies focused on the relationship between digital technology adoption, green practices, and firm performance (Azman & Ahmad, 2023; Belhadi et al., 2020). The digital technology capabilities as a mediator still need further study, where adopting the dynamic capability view (Pavlou & Sawy, 2011) enables the transformation of the green resources effects to achieve sustained performance. Adopting a quantitative study will fill the empirical gap and provide in-depth knowledge on the role of digital capabilities towards firm performance and the mediating relationship between green resources and firm performance, particularly in the automotive industry.

Recent studies focused on advanced digital-smart synergy have not been applied to automotive resource efficiency, particularly in Malaysia (Chen et al., 2025; Mai et al., 2026; Wu et al., 2025). In spite of this, many empirical studies have been conducted outside Malaysia, and the automotive industry is gaining attention as a major contributor to carbon emissions (Raziff et al., 2024). Although, past studies that concentrated on the ASEAN region and Malaysia mainly focus on manufacturing sectors are still in the early stages of adopting circular economy practices to enhance resource efficiency and achieve net-zero emissions (Jamaluddin et al., 2022; Kifor and Grigore, 2023). The results have led to a lack of green practices and ELV recovery, and circular economy barriers in Malaysia automotive industry (Mohamad-Ali et al., 2024; Raziff et al., 2024; Yahaya et al., 2024). Besides, Malaysia is still lagging behind ASEAN countries in Industry 4.0 adoption due to high investment costs and technical knowledge gaps (Adnan et al., 2023).

Table 2.1
Summary of Gap-Hypothesis Mapping

Identified Gap	**Corresponding Hypothesis**
Limited empirical evidence on green resources and the effect on firm performance, particularly focusing on the Malaysian automotive industry.	H1: Green resource usage positively influences the performance of automotive firms.
Digital technology capabilities are underexplored as a mediator, particularly the integration between green resources and firm performance.	H2: Green resource usage positively influences the digital technology capabilities of automotive firms. H4: Digital technology capabilities mediate the relationship between green resource usage and automotive firm performance.
Inconsistent findings on whether digital technology capabilities directly enhance the firm performance or require activation mechanisms.	H3: Digital technology capabilities positively influence the performance of automotive firms H4: Digital technology capabilities mediate the relationship between green resource usage and automotive firm performance.

Thus, this study focuses on the Malaysian automotive industry to investigate the effect of green resources and the mediating role of digital technology capabilities in enhancing firm performance. This research will provide comprehensive insights for stakeholders, policymakers, and future researchers.

2.4 Hypothesis Development

Drawing from underlying theories and previous literature reviews, Figure 2.2 illustrates the Green-Digital conceptual framework developed for this research. This study addresses the research question and objectives. The RBV theory posits that resources are valuable, rare, inimitable, and non-substitutable organisational capabilities, providing a sustainable competitive advantage (Barney et al., 2001; Newbert, 2007). Green resources are considered valuable, rare, inimitable, and organisation-specific assets in the automotive sector. These green resources in automotive firms directly contribute to both financial and non-financial performance, particularly in terms of operational efficiency (Alos-Simo et al., 2020; Khan et al., 2022).

The contradictory findings may suggest that the effect of operational performance is stronger than financial contributes to overall firm performance, given that Malaysia is still in the early stages of circular economy practices (Jamaluddin et al., 2022; Kifor & Grigore, 2023). Enhanced firm performance ultimately leads to improved industry competitiveness. In conclusion, this study investigates the effect of green resource usage on the performance of automotive firms. The following hypothesis was developed based on the discussion.

H1: Green resource usage positively influences the performance of automotive firms.

However, RBV and DCV fold to elucidate how an organisation can maintain its competitive edge in a dynamic environment over time. The tenuous connections between resources and firm performance necessitate robust technology capabilities to achieve a competitive advantage. In the current Industry 4.0 era, the incorporation of digital technology tools can optimise resource utilisation (El-Kassar and Singh, 2019; Umar et al., 2022). Digital technology capabilities demonstrate the automotive firm's capacity to identify opportunities for green resource optimisation, employ learning to enhance green processes, integrate green resources with operational systems via digital platforms, and coordinate green strategies across organisations using digital tools to achieve resource efficiency. However, a lack of management skills and necessary tools hindered the green resource optimisation, requiring firms to invest in digital capabilities to achieve firm performance (Pathak et al., 2021). The following hypothesis was developed based on the discussion.

H2: Green resource usage positively influences the digital technology capabilities of automotive firms.

The Industrial Revolution 4.0 enablers, digital technologies encompass a set of smart technologies, particularly Big Data, the Internet of Things (IoT), Cyber-Physical Systems (CPS), and Cloud Computing, to transform traditional manufacturing into a digitalised manufacturing process (Hamdi et al., 2019; Li et al., 2020). Numerous studies have proved that the adoption of digital technology positively enhances firm performance (Bag et al., 2020, 2021). Consistent with past studies, the direct effects might not be significant in the presence of mediation (Y. Li et al., 2020; Setiawan et al., 2025).

Leveraging digital technology capabilities within organisations is important to improve automotive firms' production processes and achieve a competitive advantage. The firm will perform better in terms of operational performance and financial performance. The operational performance will be improved through delivery time, flexibility, production quality, operational cost, and carbon emissions. Meanwhile, financial performance will be improved in terms of profitability, sales, market share, and return on investment. The following hypothesis was developed based on the discussion.

H3: Digital technology capabilities positively influence the performance of automotive firms.

Meeting the net-zero emission and emergence of a circular economy, this study positions digital technology capabilities as a mediator, offering a robust mechanism to explain how automotive firms maximise the efficiency and effectiveness of green resources to enhance financial and operational performance. Consequently, the efficiency of green resources, facilitated by digital technology capabilities, enhances the automotive firm's competitive advantage, enabling it to compete effectively in the market to improve its financial and non-financial performance. Green resources alone may not be fully optimised without the digital capabilities (Kankanamge et al., 2026). Leveraging internal resources with robust and new technology can close the loop to improve resource efficiency and reduce carbon emissions (Okorie et al., 2023). The following hypothesis was developed based on the discussion.

H4: Digital technology capabilities mediate the relationship between green resource usage and automotive firm performance.

2.5 Conceptual Framework

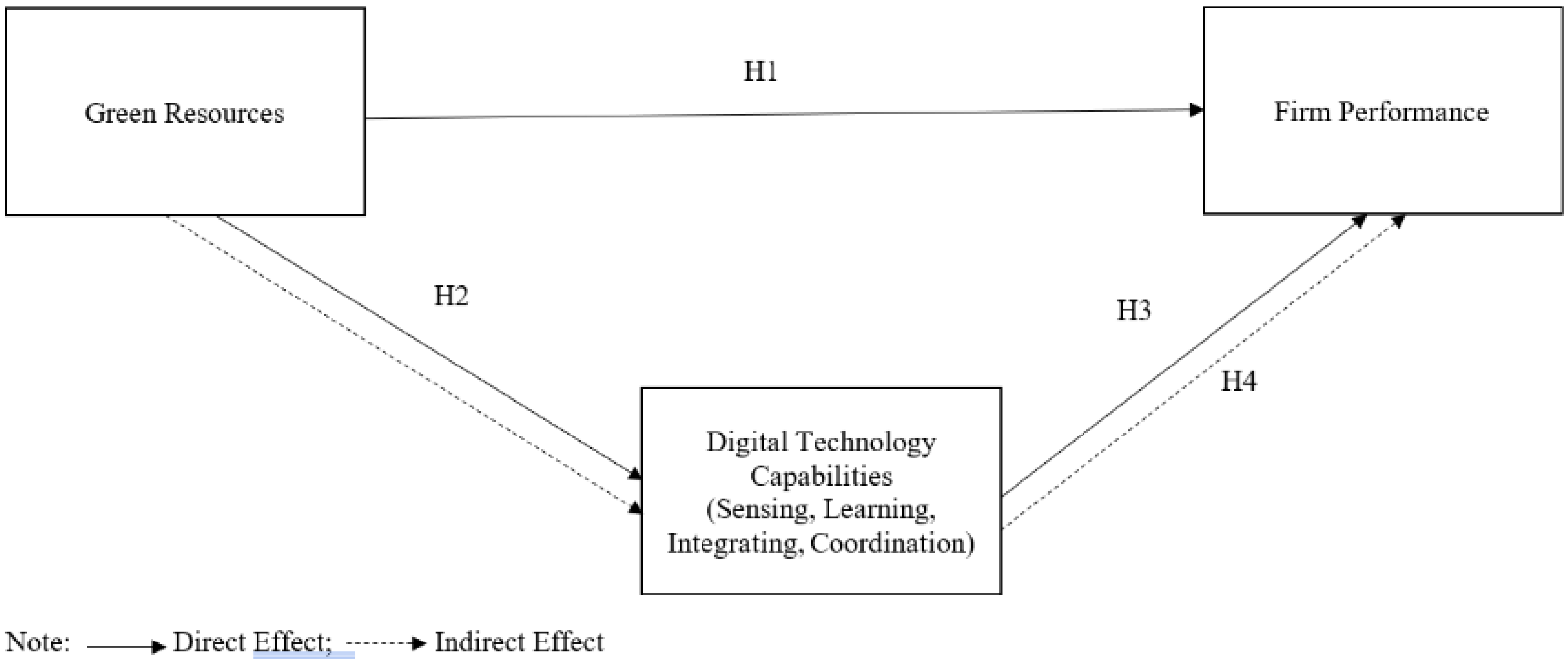


Figure 2.4: Green-Digital Conceptual Framework

2.6 Chapter Summary

This chapter explores the theoretical and empirical groundwork for investigating the interrelationship among green resources, digital technology capabilities, and firm performance within the Malaysian automotive industry. The research is underpinned by an integrated Resource-Based View (RBV) and Dynamic Capabilities (DCV) framework. Drawing on the gap hypothesis mapping, four hypotheses were formulated. Specifically, H1 seeks to address the limited empirical evidence on green resources and firm performance, particularly in the automotive industry in Malaysia. Besides, H2 responds to the underexplored role of digital technology capabilities as the mediator in evaluating how green resources influence digital capabilities. The H3 addresses the inconsistent findings on whether digital capabilities directly enhance performance. While H4 tests the mediator effect of digital technology capabilities as the mechanism through which green resources translate into firm performance, differentiating resource possession (RBV) from resource activation (DVC). The critical synthesis of past empirical studies revealed that green resources consistently enhanced operational performance but showed an uncertain financial effect. However, both dimensions collectively contribute to enhanced firm performance. The digital technology capabilities demonstrated stronger indirect effects through mediation than direct effects. This theoretically rigorous framework lays the groundwork for the research methods employed to test these hypotheses.

CHAPTER 3

RESEARCH METHODOLOGY

3.0 Introduction

This section delineates the methodology employed to investigate the relationships between green resources, digital technology capabilities, and firm performance in the Malaysian automotive industry. It commences with an overview of the study's paradigm and design, followed by a detailed step-by-step process undertaken throughout the investigation. This process encompasses data gathering techniques and sample selection criteria. The chapter also incorporates the discussion on research instruments, variable measurement, and concludes by explaining the model and statistical analyses that will be applied to examine the collected data.

3.1 Research Paradigm

Research philosophy encompasses the discussion of assumptions and beliefs derived from the conceptual framework to guide the contribution of new knowledge in specific research domains (Ragab and Arisha, 2017; Saunders et al., 2019). Research philosophy is fundamental and critical for researchers to construct a research method approach that examines the formulated research questions. According to Orlikowski and Baroudi (1991), these assumptions and beliefs derived from the conceptual framework constitute the object of study, which supports theoretical knowledge and addresses the interconnection between theory and empirical investigation (Alharahsheh and Pius, 2020). Positivism, constructionism, critical realism, and pragmatism are the research paradigms extensively discussed by business researchers (Sekaran and Bougie, 2016).

The research paradigm adopted for this study is based on the positivism paradigm. This paradigm is consistent with the nature of the inquiry and the research objectives. The positivist paradigm emphasises that the world is observably real, and researchers need to measure and verify the theory so that their values, beliefs, and biases will not affect the research findings (Saunders et al., 2019). The positivist approach is instrumental in generating knowledge through systematic and objective procedures, enabling researchers to confirm the relationships between variables in a structured manner.

As it relates to this study, ontology refers to the nature of reality and what can be known about it. Within the positivist paradigm, the ontological assumption is that reality is objective, external, and independent of human perceptions or beliefs. This perspective aligns with the study's aim to explore cause-and-effect relationships and validate the theoretical framework through empirical measurement. The belief in an external reality that can be observed and measured underpins the choice of a quantitative methodology.

In this regard, the empirical findings of this research study will enrich the interconnection and contribution to the notion of knowledge. Ontologically, this research filled in the gap and contributed to the knowledge of the existence of reality (Ragab and Arisha, 2017) in the automotive industry scenario in Malaysia. The Industrial Revolution reflects the adaptations of firms to modify their resources and the capability to reform the resources dynamically to influence the firm's performance. Subsequently, the objectivism of this study is to grasp the reality, to investigate to what extent the automotive firm has adapted towards the digital transformation, and how the current changes will portray the overall industry, and such changes are not transferable to the social world.

In this light, empirical epistemology discusses deductive research to obtain research's rigour, replicability, reliability, and the generalisation of the findings (Bougie and Sekaran, 2019). Consequently, this study is based on the deductive theory approach (Ragab and Arisha, 2017; Rahi, 2017; Saunders et al., 2019), as the positivist paradigm focuses on theory testing and verifying the research hypotheses, as depicted in Figure 3.1. Deductive reasoning involves developing hypotheses based on existing theories and then testing these hypotheses through empirical observation and analysis. This method is particularly suitable for studies grounded in the positivist paradigm, as it systematically tests theoretical propositions to confirm or refute them. The deductive approach ensures that the research progresses logically from the general (theoretical framework) to the specific (empirical findings), maintaining a clear alignment with the research objectives.

This study investigates the underlying Resource-Based View (RBV) and Dynamic Capabilities View (DCV) perspectives on firm performance in the automotive industry. Four research hypotheses were developed based on previous studies. The hypotheses, derived from the theory, reflect the nature of reality. These hypotheses were formulated to examine the effect of green resources on automotive firms' performance, the impact of green resources on the digital technology capabilities of automotive firms, the influence of digital technology capabilities on automotive firm performance, and the effect of green resources on automotive firm performance when mediated by digital technology capabilities.

This study employs a quantitative approach to validate the proposed theoretical framework through empirical observation and measurement (Alharahsheh and Pius, 2020). The positivist paradigm aligns with the research objectives, facilitating the use of quantitative methods to investigate cause-and-effect relationships and test hypotheses. The primary aim of the research is to examine the interrelationship between green resource utilisation, digital technology capabilities, and the performance of automotive firms. These elements constitute the study's theoretical framework, which the research seeks to empirically validate. This investigation's scope is confined to Malaysia's automotive industry, providing sector-specific insights.

Survey questionnaires were utilised to collect data. The questionnaires were designed and administered to a targeted sample of respondents within the Malaysian automotive industry. The survey instrument was meticulously developed to ensure a comprehensive and accurate capture of the relevant variables. Through the use of standardised questions and scaling methods, the study ensures consistency and reliability in the data collection process. The survey responses serve as the study's primary dataset, enabling various statistical tests to measure the cause-and-effect relationship between green resource utilisation, the role of digital technology capabilities, and the performance of automotive firms to derive meaningful findings.

The study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) as the primary analytical tool. PLS-SEM is particularly appropriate for examining complex relationships and testing mediation effects (Ramayah et al., 2018). This approach enables the research to analyse the direct effect of green resource utilisation (independent variable) on firm performance (dependent variable) and the mediating role of digital technology capabilities. Statistical tests, including descriptive and PLS-SEM path analyses, were performed to examine the hypotheses and draw meaningful inferences. These techniques facilitate the identification of significant relationships between the variables, thereby providing empirical evidence to support or refute the theoretical propositions.

The quantitative methodology employed in this study aligns with the positivist paradigm's emphasis on objectivity, replicability, and generalisability. The research mitigates subjective bias and enhances the reliability of the findings by quantifying constructs and applying rigorous statistical procedures. Furthermore, using a structured and standardised approach ensures that the results are internally valid and externally applicable to comparable contexts within the automotive industry.

In conclusion, this study exemplifies a positivist research paradigm, utilising a deductive approach, survey method, and quantitative analysis employing PLS-SEM to validate the proposed theoretical framework. By examining the causal relationships between green resource usage, digital technology capabilities, and firm performance within the Malaysian automotive industry, the research contributes to the existing body of knowledge and provides practical insights for the sector. This paradigm and methodology establish a robust foundation for achieving the research objectives and ensuring the scientific validity of the findings.

3.2 Research Design

Specifically, the research method explained the method used to conduct the study (Basias and Pollalis, 2018). This study employed a quantitative method. The quantitative research method is widely utilised in business and social studies. The research hypotheses were examined to obtain exploratory, predictive or confirmatory research outcomes (Ragab and Arisha, 2017). Consequently, there are three types of research objectives: exploratory research, explanatory research and descriptive research. Explanatory research is adopted for this study as the research objectives and research questions are developed to investigate the effects among the variables and relate them to reality to contribute new insights. Conversely, explanatory research aims to provide justification based on the causal relationship, while descriptive research portrays the background profile of the research study (Ragab and Arisha, 2017; Rahi, 2017). This research examines the relationship between two characteristics of the research study (Williams, 2007). Thus, validity and reliability are crucial to determine the effect of the relationship.

In this research context, due to the lack of past literature studies on green resource usage and digital technology capabilities, the explanatory research method will enable the researcher to investigate reality and seek new insights. As such, the research questions are developed to support the RBV and DC perspectives to provide a better understanding of the effect of green resource usage on firm performance and its relationship with digital technology capabilities. Secondly, the effect of digital technologies' role as a dynamic capability on firm performance, and lastly, the mediation relationship between the green resources' consumption and digital technology capabilities on firm performance.

To complement the explanatory study, the descriptive study method will also be utilised to discuss and provide information on the current state of automotive firms. The information on the firm's profile, such as the types of digital technologies adoption and the current implementation of green initiatives and the firm's profile, will be substantial to provide the overview scenario of the automotive firms in the industry. The profile information will be significant in explaining the implications and the contribution to this study as well. According to Sekaran and Bougie (2016), descriptive studies enable the researcher to better understand the characteristics of certain groups in the research study. The given background information will enable the researcher to assess analytically the aspects that are needed in the research study, to provide insights for further research, and inherently make more informed decisions.

3.2.1 Research Survey

Research strategy is a process of data collection and interpreting the information to fulfil the research objectives (Rahi, 2017). A few types of research strategies are in the research, such as experiments, surveys, case studies, action research, grounded theory, ethnography, and archival research. Subsequently, this research study uses a deductive approach that uses explanatory and descriptive research methods; hence, the survey strategy was adopted (Saunders et al., 2008). Therefore, a pre-designed questionnaire was used in this study as the strategy to gather the information quantitatively and analyse it using descriptive and inferential statistical analysis (Saunders et al., 2008). Using this strategy enables the researcher to control the research process method to ensure the data collection data resembles the overall population at a lower cost (Saunders et al., 2008). In such cases, the researcher needs to spend time designing and piloting the data instrument to give a better generalization.

To execute the research strategy, the time horizon enables the researcher to plan when to conduct the research (Saunders et al., 2008). The time horizon consists of a cross-sectional survey study and a longitudinal survey study. Research that is carried out over time is a longitudinal study, while a study at that point in time is a cross-sectional study. Most of the past studies were related to green manufacturing and digital technologies at the point of a particular time (Alos-Simo et al., 2020; Bag et al., 2021; Dawal et al., 2015; Dunaway Virginia et al., 2019; Habidin et al., 2016, 2018; Zailani et al., 2015), which refers to a cross-sectional study. Hence, this study is also based on a cross-sectional study since the researcher intends to study on particular phenomenon at that point in time among the automotive firms.

3.2.2 Self-Administered Questionnaire

The self-structured questionnaire is widely used for descriptive and explanatory research. The self-administered questionnaire is a structured survey question that will be administered to collect primary data (Rahi, 2017). In this study, close-ended questions are constructed to observe the automotive manufacturing firms. The questionnaire can be disseminated electronically through the internet, through postal or by hand and collected later (Saunders et al., 2008). On the other hand, to increase the response rate and to ensure the validity and reliability of the data, the questionnaire is designed sensibly to assess the research questions. On top of that, the self-administered questionnaire is appropriate for gathering information within the geographical area because this approach is effective and efficient in terms of cost and time (Abdul-Rashid et al., 2017).

3.2.3 Unit of Analysis

The unit of analysis ultimately represents "what" or "whom" is intended to be studied within the population (Trochim and Donnelly, 2006). In this study, the unit of analysis was the automotive firms. The automotive industry is a rapidly evolving sector in Malaysia, and it is potentially necessary to examine the impact of green resource consumption and the role of digital technologies. This industry also significantly contributes to environmental pollution in Malaysia (Mohamad-Ali et al., 2024; Raziff et al., 2024; Yean, 2021).

3.2.4 Population and Sampling

The population is individuals or entities that the researcher intends to investigate (Rahi, 2017). In this study, the automotive industry comprises approximately 679 firms, encompassing 38 vehicle manufacturers or assemblers, 641 parts suppliers, and component suppliers (MITI, 2023). According to the New Industrial Master Plan (NIMP) 2030, the automotive industry is a significant contributor to the manufacturing sector, as it plays a crucial role in Malaysia's economic growth and employs approximately 102,081 workers as of 2022 (MITI, 2023). Concurrently, it substantially contributes to environmental emissions due to the excessive consumption of resources and energy (Madrid, 2023).

3.3 Sampling Design

Sampling is a process of selecting a representative subset from the population (Rahi, 2017). The sampling design provides the framework for the research study in the sampling process. According to Taherdoost (2017), the sampling process comprises six steps, commencing with identifying the population, determining the sampling frame, selecting the sampling technique, establishing the sample size, collecting the sample and assessing the sample to ensure it represents the population. The sampling technique encompasses probability and non-probability sampling (Taherdoost, 2017).

3.3.1 Sampling Technique

The sampling strategy employed in this study comprised purposive sampling. Purposive sampling was used for data collection, enabling participants who met the eligibility criteria (Saunders et al., 2009; Savastano et al., 2022). Specifically, managers or executives within automotive industry firms were invited to participate in the survey. These respondents were briefed on the research objectives and their potential contributions before confirming their willingness to participate. In addition, snowball sampling was frequently applied to overcome challenges in identifying potential respondents (Saunders et al., 2009). This method involved soliciting initial participants to recommend colleagues or collaborators, effectively broadening the pool of respondents and increasing the overall response rate.

3.3.2 Sampling Frame

The sample frame constitutes a subset of the target population (Rahi, 2017). In this study, the survey's intended participants are from automotive manufacturing firms operating in Malaysia. Since it is at the firm level, the respondent must be a leader, managerial or executive role from each firm that could serve as a respondent, as they are knowledgeable about their firm's green resources usage, digital technology capabilities, and firm performance within Malaysia's automotive industry. Concurrently, a compilation of automotive companies operating in the industry was gathered from various sources, as there is no standard sampling frame. The Malaysia Automotive Association (MAA) website provided a list of manufacturers and assemblers, while the Dun and

Bradstreet Business Directory website supplied information on motor vehicle parts manufacturing companies in Malaysia.

3.3.3 Sampling Unit

In sampling methodology, the unit refers to the selectable element during the process (Sekaran and Bougie, 2016). The sampling unit is an automotive firm, specifically targeting top management, managers or executives. The personnel can be from across the organisation departments, from Operations, Quality, Research and Development, Environmental Health and Safety (Rashid et al., 2015), Information Technology (Belhadi et al., 2020; Dunaway Virginia et al., 2019), or Human Resource Management (Ogbeibu et al., 2020). Thus, including the managerial level from these divisions is essential for examining various aspects of automotive industry performance. These divisions were chosen due to their comparable characteristics and perceived knowledge of green resource management initiatives and digital technology capabilities. Meanwhile, these managerial levels are knowledgeable individuals and directly engaged in planning and executing green and technology processes within their organisations (Abdul-Rashid et al., 2017; Rashidirad and Salimian, 2020; Sakrabani and Teoh, 2020; Savastano et al., 2022). Their inclusion provides a comprehensive understanding of how green resources are used and how digital technology capabilities are implemented and managed across various tiers of the organisation.

3.3.4 Sample Size

The sample size is crucial for generalisation and must be sufficiently large to prevent bias, as noted by Taherdoost (2017). It should also be carefully selected to minimise sampling error in statistical analysis (Rahi, 2017). Various methods were used to determine sample size. However, the unit of analysis in this study targeted automotive firms and focused on the managerial level using a non-probability sampling technique influenced the sample size. According to Memon et al. (2020), research related to the organisation will have a smaller sample size compared to the individual. It is also supported by Bartlett et al. (2001) that the sample size of 102 firms proposed will be sufficient based on the population. Hence, the minimum sample size for this study is 102 firms, which targeted top management or executives in automotive firms from the main departments to ensure a well-rounded understanding of organisational dynamics, enhancing the generalisation of the findings within the automotive firms (Memon et al., 2025).

At the same time, the structural equation modelling method was adopted for this study. This aligns with Memon, Ting, Cheah, Ramayah, and Cham (2020), who posited that a sample size between 150 and 300 typically yields more meaningful and robust results when utilising SEM. Consequently, it was determined that distributing to 250 firms would suffice for both reliability and comprehensive analysis, ensuring robust findings. This approach is particularly suitable for this study's objectives of analysing green resource usage, digital technologies' capabilities, and firm performance in Malaysia's automotive industry.

3.4 Measurement of the Constructs

Measurement involves collecting numerical data and using scales to distinguish respondents' answers across variables. Four scale types exist: nominal, ordinal, interval, and ratio. Ordinal and interval scales were employed for the questionnaire. Ordinal scales rank items, whilst interval scales quantify equal differences between items in a variable (Sekaran and Bougie, 2016). The questionnaire used ordinal scales for profiling, gathering company characteristics and information on green resource usage and digital technology adoption.

A seven-point interval scale was utilised for variable constructs within the questionnaire (Sekaran and Bougie, 2016). Interval Likert scales are commonly adopted in business research as a scaling measure (Sekaran and Bougie, 2016). In this study, the Likert scale is treated as an interval scale (Preston and Colman, 2000). The rationale for employing a seven-point interval scale rather than a five-point scale is twofold: (1) it more closely approximates a continuous scale, better representing the raw data with reduced correlations (Wu and Leung, 2017), and (2) it optimises reliability (Preston and Colman, 2000). This choice aligns with previous studies that have used 7-point interval Likert scales for Structural Equation Modelling (SEM) analysis (Dunaway Virginia et al., 2019; Habidin et al., 2015; Rashid et al., 2015).

3.4.1 Research Instruments

This research proposes green resource usage as the latent construct, with digital technology capabilities serving as the mediating variable construct. The study's endogenous construct is the firm performance of automotive firms. The research framework comprises three constructs, one of which is multi-dimensional, as illustrated in Table 3.1. All items within these constructs have been adopted and modified from previous literature to address and align with the study's research questions, objectives, and hypotheses. The questionnaire developed for this investigation (Appendix A) is divided into four sections. The initial section evaluates firm performance, followed by an assessment of green resource consumption in automotive firms. The third section examines the role of digital technology capabilities, whilst the final section gathers profile information about the companies.

Table 3.1

Summary of Measurement of Variables

Section / Construct	Quantity of items	Focus of Items	Types of Scale
A: Firm Performance	12	The dependent variable	Interval
B: Green Resources	14	The independent variable	Interval
C: Digital Technology Capabilities	24	The mediating variable	Interval
D: Demographics	9	The firms' information and the respondents' demographic	Ordinal and Nominal

Instrument for Independent Variable: Firm Performance

The instrument for the firm performance consists of 12 items, as depicted in Table 3.2. The measurement of this construct using an interval scale ranging the Likert scale point from 1 point, “Strongly Disagree”, to 7 points, “Strongly Agree”, and the measurement items were adopted and adapted from Felsberger et al. (2020) and Khan et al. (2021).

Table 3.2

Summary of Instrument of Firm Performance

Main Constructs	Item Label	Statements Currently, our firm…………..	Source
Firm Performance (FP)	FP1	Achieved the targeted profit growth.	Felsberger et al. (2020) and Khan et al. (2021)
	FP2	Achieved the targeted sales growth.	
	FP3	Achieved the targeted return on investment.	
	FP4	Achieved the targeted market shares.	
	FP5	Overall financial performance improved.	
	NFP6	Improved the product quality.	
	NFP7	Improved in operational cost reduction.	
	NFP8	Improved the speed of production process.	
	NFP9	Improve wastage reduction	
	NFP10	Improve energy usage	
	NFP11	Improve the competitiveness of business	
	NFP12	Overall non-financial performance improved	

Instrument for Dependent Variable: Green Resources Usage

The instrument for green resource usage consists of 14 items, as depicted in Table 3.3. The measurement of this construct is using an interval scale ranging the Likert scale point from 1 point, 1 point, “Strongly Disagree”, to 7 points, "Strongly Agree". The measurement items were adopted and adapted from El-Kassar and Singh (2019), Habidin et al. (2018), and Hassana et al. (2016).

Table 3.3

Summary of Instrument for Green Resources

Main Constructs	Item Label	Statements Our firm …………..	Source
Green Resources (GR)	GR1	uses environmentally friendly resources.	El-Kassar and Singh (2019), Habidin et al. (2018), and Hassana et al. (2016)
	GR2	uses renewable resources.	
	GR3	uses reusable parts.	
	GR4	recycle the waste.	
	GR5	saves the use of energy.	
	GR6	saves the use of water.	
	GR7	uses technology in the production operation processes to reduce pollution and emission.	
	GR8	uses technology to save energy, water, and waste.	
	GR9	invest in R&D projects to achieve environmentally friendly operations.	
	GR10	have well skilled workers to achieve resource efficiency.	
	GR11	have well experienced workers to achieve resource efficiency.	
	GR12	have well skilled workers in developing green products and processes.	
	GR13	have well experienced workers in developing green products and processes.	
	GR14	Overall, our firm improved resource efficiency.	

Instrument for Mediator Variable: Digital Technology Capabilities

The instrument for the role of digital technology capabilities consists of 24 items, as depicted in Table 3.4. The measurement of this construct is using an interval scale ranging the Likert scale point from 1 point, 1 point, “Strongly Disagree”, to 7 points, “Strongly Agree”. The measurement items were adopted and adapted from Pavlou and Sawy (2011), Rashidirad and Salimian (2020), and Schmidt and Scaringella (2020). The sub-construct consists of sensing, learning, integrating and coordinating. Each sub-construct represents 6 items.

Instrument for Key Information of Profile

The instrument for the key information of the profile comprises 9 items, as presented in Table 3.5. The measurement of this construct utilises an ordinal scale. The demographic variables are derived from extant literature (Abdul-Rashid et al., 2017; Ahmad et al., 2022; Chauhan et al., 2021; Fernando et al., 2019; Rashidirad and Salimian, 2020; Sakrabani and Teoh, 2020; Savastano et al., 2022) and National Automotive Policy 2020 (MITI, 2020), which was modified accordingly to meet the research requirements.

Table 3.4

Summary of Instrument for Digital Technology Capabilities

Construct	Sub-construct	Item	Statements	Source
Digital technology capabilities (DC)	Sensing (SC)	SC01	Frequently scan environment to identify opportunities.	Pavlou and Sawy (2011), Rashidirad and Salimian (2020), and Schmidt and Scaringella (2020)
		SC02	Periodically review the likely effect of the customers.	
		SC03	Review products development efforts	
		SC04	Detect changes in customers' preferences	
		SC05	Observe customers' needs.	
		SC06	Improved overall sensing capabilities.	
	Learning (LC)	LC01	Have effective routines to identify new information and knowledge.	
		LC02	Have effective routines to value new information and knowledge.	
		LC03	Have adequate routines to assimilate new information and knowledge.	
		LC04	Effective in using knowledge into value creation (new product and process)	
		LC05	Effective in developing new knowledge	
		LC06	Improved overall learning capabilities.	
	Integrating (IC)	IC01	Contribute individual input to the firm.	
		IC02	Integrate with the new information and knowledge acquired.	
		IC03	Integrated information in the firm.	
		IC04	Have effective communication between individuals.	
		IC05	Being aware of who in the firm has specialized skills and knowledge.	
		IC06	Improved overall integrating capabilities.	
	Coordinating (CC)	CC01	Ensure the output of work is synchronized with the work of others.	

CC02	Ensure an appropriate allocation of resources (e.g., information, time, reports).
CC03	Ensure the compatibility between expertise and work process.
CC04	Assign employees to tasks that appropriate with their task-relevant knowledge and skills.
CC05	Coordinate all the firm's functions.
CC06	Improved overall firm's coordinating capabilities.

Table 3.5

Summary of Key Information Profile

Variables	Items	Descriptions	Source
Demographics	Number of employees (Firm Size)	Less than 51 51-150 151-250 251-500 More than 500	(Abdul-Rashid et al., 2017)
	Firm's Establish year	Less than 1 year 1-5 years 6 – 10 years 11 – 15 years 16 years above	(Fernando et al., 2019)
	Ownership	Local Foreign	(Abdul-Rashid et al., 2017)
	Current Department/Division	Operational Quality Research and Development Environment Health and Safety Information Technology Human Resource	(Rashidirad and Salimian, 2020; Sakrabani and Teoh, 2021; Savastano et al., 2022)
	Current Managerial Position	Top Manager Sub Manager Middle Manager Executives Junior Executives	Rashidirad and Salimian, 2020; Sakrabani and Teoh, 2021; Savastano et al., 2022
	Work experience	Less than 1 year 1-5 years 6 – 10 years 11 – 15 years 16 years above	(Fernando et al., 2019)

Types of digital technology adopted	Internet of Things Big data and analytics Cyber-Physical System Cloud Computing Additive Manufacturing Simulation and autonomous robot Artificial Intelligence System Integration Augmented Reality Advanced Materials	(MITI, 2020)
Type of environmental initiatives/practices	Lean production Life Cycle Assessment Environmental Management System (EMS) Emission reduction Water Management Material Efficiency Product Recovery (recycling, reuse and remanufacturing) Others	(Fernando et al., 2019)
Challenges in digital technologies adoption	Lack of Finance Lack of Information Lack qualified employee Cyber security Standardization problem Research and Education Costs	(Ahmad et al., 2022; Chauhan et al., 2021)

3.4.2 Pre-testing

The pre-test was conducted prior to the distribution of the questionnaires. This is to assess the relevance and comprehension of the survey instruments. Ensuring that all instruments are developed to measure the particular variable accurately is essential. The measurement should be clear, concise, and comprehensible to increase the response rate (Rubio et al., 2003). Consequently, it is crucial to validate the instrument measurement to determine whether the accuracy of the measured variable is truly achieved. Validation can be categorised primarily into three categories: content validity, criterion validity, and construct validity

(Sekaran and Bougie, 2016). Nevertheless, the pilot test is required to be conducted on a sample to provide feedback to the pilot testing. The data collected from the pilot test needs to be examined for validity and reliability (Saunders et al., 2009).

Content Validity

Content Validity is a measure of the extent to which the items adequately represent the variable of the research (Rubio et al., 2003). The majority of researchers conduct content validity to validate their questionnaires (Belhadi et al., 2020; Dubey and Bag, 2017a; Singh and El-Kassar, 2019; Valase and Raut, 2019). Taherdoost (2018) asserts that content validity needs to be conducted to evaluate new instruments developed for research. As such, adopted measurement items are typically based on previous literature reviews and, therefore, require validation from experts to confirm the items measured in the study. The expert panel evaluates the questionnaire item measurements and provides suggestions for improvement (Rubio et al., 2003). The revised survey can subsequently be utilised for the pilot study. Thus, there are several steps to conduct content validity. First, a panel of experts must be selected. Subsequently, one must request the participation of experts before conducting the analysis.

Rubio et al. (2003) recommend identifying a minimum of three (3) experts for each group to produce a sample size ranging from 6 to 10 to generate more information regarding the measurement items. In this research, in compliance with the suggested requirement, six (6) experts were selected to evaluate the quantitative measurement items. A cover letter is included with the questionnaire explaining the purpose of the research, providing instructions for completion and assuring that the received information will be used solely for purposes of scientific research. Table 3.6 summarises the feedback suggested by the experts and corrections. The revision ensures the clarity and appropriateness of the survey items.

Table 3.6
Summary of feedback arising from pre-testing

Section	Recommendations/Suggestions	Correction made
Cover Letter	Suggested adjusting the research title to "The impact of green resources and the role of digital technology capabilities on the firm performance among Malaysia Automotive Firms"	Revisions have been made as suggested.
Section A: Firm Performance	Suggestion to amend/add description on the following: Ensure the variable has not less than 5 items Remove QFP5: Achieved the targeted penetration rate. The labelling of items needs to be separated between FP and NFP. FP9: "Improve resource (waste and energy) efficiency" required to be split into separate resources such as reduced wastage, energy, etc. Add in "overall non-financial performance improved". Change the scale to 7 Likert-scale	Revisions have been made as suggested.
Section B: Green Resource	Suggestion to amend/add description on the following: Ensure the variable has not less than 5 items Use simple sentences GR7 and GR8 appeared similar items and occurred double barrel question – GR 7 removed and GR 8: "uses technology in the production operation processes to reduce pollution and emission" was refined and remained. Suggested to have the same points of scale throughout the questionnaire	Revisions have been made as suggested.

	QGR11: "have well trained skilled and experienced workers to achieve resource efficiency" required to split into two between skilled and experienced QGR12: "Have well skilled and experienced workers in developing green product and process" required to split into two between skilled and experienced. QGR13: "firm improved performance in resource efficiency and environmentally" need to be refined to "improved resource efficiency".	
Section C: Digital Technology Capabilities	Suggestion to amend/add description on the following: Ensure the variable has not less than 5 items ASC01: "Frequently scan environment to identify new business opportunities" refined to "frequently scan environment to identify opportunities". ASC02: "Periodically review the likely effect of the changes on customers" refined to "Periodically review the likely effect of the customers". ASC04: "Detect changes in customers' product preferences" to "Detect changes in customers' preferences". ASC05: "Observe customer's needs and problems" required to focus either customer's needs or problem. ASC06: "observe competitors" suggested to remove. ALC01: "Have effective routines to identify, value, and import new information and knowledge" appared to be double barrel questions. Suggested to separate the focus to avoid misled. AIC02: "Integrate existing knowledge with the new information and knowledge acquired" suggested to remove"existing knowledge" AIC04: "Integrated information and knowledge resources to the entire wide of the firm" suggested to refined to reflect integrated information in the firm. AIC05: "Have informal and direct communication between	Revisions have been made as suggested.

	individuals" suggested to be refined to reflect effective communication between individuals. ACC05: "Have a well-coordinated firm" and ACC07: "Improved overall coordinating capabilities" seem similar. Suggested to remove ACC05.	
Section D: Demographic	Suggestion to amend/add description on the following: List the current department/division for Q4. List the current managerial position for Q5. Suggested to use top 5 management position in a manufacturing company for Q5. List experience years for Q6. List the type of digital technologies adopted for Q7. List type of environmental initiatives/practices for Q8.	Revisions have been made as suggested.

Note: "Q" refers to the question number and "A" refers to the attribute number

3.4.3 Pilot Test

Regarding pilot studies, a limited sample size is necessary for preliminary testing prior to conducting a comprehensive field study (Bamgbade et al., 2015; Phankhong et al., 2020). Previous research indicates that a sample of 30 to 100 participants is adequate to evaluate the validity and reliability of study items before the main investigation (Bamgbade et al., 2015). Consequently, a sample of 30 firms is deemed suitable for the pilot study for gathering preliminary data and making essential adjustments before the actual survey commences.

After the content validation, modifications were implemented as necessary, and certain items were revised, filtered, relocated or removed from the suggestions provided by the experts. Subsequently, a pilot test was conducted in late August 2022. Thirty respondents were selected randomly from automotive firms located in Tanjung Malim, Perak. The participants were provided with a brief introduction prior to being requested to complete the questionnaire. Upon completion of the questionnaire, the researcher inquired whether the layout, content, and other components of the questionnaire were unclear to the respondents. The instructions proved to be comprehensible, as none of the respondents raised any queries or expressed hesitation.

The pilot test outcome is summarised in Table 3.7. The Cronbach's coefficient alpha test assesses the consistency of all the items in a measure, where the closer the value is to 1, the higher the internal consistency reliability (Bougie and Sekaran, 2019). The reliability of the constructs ranged from 0.963 to 0.989, which falls within the accepted range, indicating that all the items are measurements of the same construct. However, assessing the validity and reliability of the pilot study was not feasible due to the insufficient sample size. Subsequently, the researcher evaluated the validity only after the final data collection phase.

Table 3.7
Summary of Reliability Analysis of the Pilot Study

Variable	**Number of items**	**Cronbach's alpha value**
Firm Performance	12	0.963
Green Resource	14	0.968
Digital Technology Capability	24	0.989

3.4.4 Ethical Clearance Procedures

Upon the pre-testing feedback, the questionnaire was finalised. The finalised questionnaire items were submitted with the application form to the UTAR Scientific and Ethical Review Committee for recommendation and approval. The data collection commenced upon receipt of the approval. After getting the approval, reference number: U/SERC/154/2022, the questionnaire items were distributed to the respondents for the field survey.

3.5 Data Collection Procedure

This study employed purposive sampling, targeting top management, managers, or executives from across the organisation departments and managerial levels who are knowledgeable and directly engaged in planning and executing green and technology processes within their organisations. The data collection was conducted from January 2023 to March 2024. Initially, questionnaires were distributed electronically by sharing the online survey link through the official human resource email address or webpage resources of automotive firms. Survey questions were also emailed to automotive firms to encourage participation from personnel in managerial positions, specifically. However, despite frequent follow-ups, the response rate remained insufficient during this phase.

To address these challenges, the questionnaires were administered subsequently in stages. The distribution was carried out between October and December 2023, focusing on automotive firms in northern (Johor Bahru, Malacca, Negeri Sembilan) and central Malaysia (Selangor and Kuala Lumpur) and between

January and March 2024 for those in southern Malaysia (Perak, Kedah, Pulau Pinang). The distribution targeted manufacturers and assemblers, components and parts manufacturers, suppliers of parts consisting of plastics parts, rubber parts, interior and exterior parts, chassis parts, batteries, body kits, electric and electronics, and other general parts. During each visit, the research objectives were briefed to the firm's Division personnel to request permission for survey participation. Questionnaires were distributed only upon obtaining the necessary permission and ensuring the willingness to participate. To enhance representativeness, a snowball sampling technique was incorporated, where respondents recruited additional managerial roles from other automotive parts and supplier firms within the automotive industry to participate in the survey. Consequently, 250 questionnaires were distributed to firms, and 190 were received. As such, only 178 were subsequently used for analysis after the data processing. The required sample size is 102 firms, but the returned questionnaires were sufficient. Moreover, as this study adopted the structural equation modelling method, the received and usable questionnaire for this study aligned with Memon, Ting, Cheah, Ramayah, and Cham (2020), who posited that a sample size between 150 and 300 typically yields more meaningful and robust results when utilising SEM.

3.6 Non–Response Rate and Common Method Bias

Non-Response Rate

The Armstrong and Overton (1977) method assessed non-response bias. Since the data was collected between October and December 2023 and January and

March 2024, using it is essential to ensure that non-response bias does not occur. The non-response can be kept below 30% if the appropriate procedure is conducted. The extrapolation method using wave analysis was adopted. An independent sample T-test was used to evaluate the differences in chosen demographic attributes between those who responded early and those who responded late to the survey.

Common Method Bias

Common Method Bias (CMB) can influence the relationship between variables due to measurement methods, especially survey studies. Podsakoff et al. (2003) implemented several recommendations to address common method variance. The questionnaire uses diverse scale types, validates the questionnaire for clarity, and guarantees respondent anonymity. However, statistically, Harman's one-factor test was used. An exploratory factor analysis examines the un-rotated factor to determine the factors necessary for the variables' variance that will suggest the presence of common method bias. The CMB may be present if one factor accounts more than 50% of the variance. In the presence of CMB, the Variance Inflation Factor (VIF) for the constructs was evaluated using the random variable technique proposed by Kock (2015). As the study adopted, Partial Least Squares Structural Equation Modelling (PLS-SEM) and the Hierarchical Component Model (HCM) were used to examine the impacts.

3.7 Data Processing

After data collection, the information was processed and transformed into valuable data for statistical analysis (Saunders et al., 2009). The completed questionnaires were reviewed to ensure the feedback met the research requirements. Subsequently, data editing and processing were necessary in the following stage to enhance data accuracy.

The acquired data required examination, and any outliers were to be removed. Subsequently, numerical codes were assigned to the collected questionnaires. This data coding process would reduce errors and the time required to transfer information into the system for transcription purposes. The information collected from the questionnaires was entered into IBM SPSS Statistics version 27 software, downloaded in Microsoft Excel files and transferred into Smart PLS version 4.0 for data analysis.

3.8 Data Analysis

Data analysis is requisite for systematically extracting useful information through statistical techniques (Bougie and Sekaran, 2019). The process of data analysis is fundamental to addressing the research hypothesis. This study incorporates both descriptive and inferential analyses.

3.8.1 Descriptive Analysis

Regarding descriptive analysis, the information in Section D of the questionnaire was analysed using descriptive statistical methods. This analysis is necessary to elucidate the general characteristics of the respondents in the study (Bougie and Sekaran, 2019).

Consequently, the respondents' demographic and firm profiles for this study were summarised using the frequency distribution method. Furthermore, the analysis also presents the mean and standard deviation of the constructs.

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

In the context of this study, the Partial Least Square Structural Equation Modelling (PLS-SEM) method was employed, utilising the Smart PLS 4.0 version tool for analysis. According to Ramayah et al. (2018), the advantages of utilising PLS-SEM can be summarised based on five criteria: research objectives, measurement model specification, structural model, data characteristics, and model evaluation. Similarly, previous research adopted PLS-SEM primarily due to small sample size, theory exploration or extension, non-normal data, and categorical variables (Ringle et al., 2018).

In comparison to covariance-based structural Equation Modeling (CB-SEM), PLS-SEM was deemed more appropriate for this study. The justifications for employing the PLS-SEM method are:

1. This study is an explanatory research that relies on prediction, theory development, and explanation.
2. The generated sample size of this study is 190 based on the inverse root square.

3. The structural model for this study consists of direct and indirect effects.
4. In this research, a formative construct is specified. Type 2, Reflective-Formative Hierarchical Component Model (HCM) model was used.
5. A bootstrapping method was used to approach the data normality. The bootstrapping is a random resampling process. Large subsamples are taken from the sample to determine bootstrap standard errors, in the result gives the structural path a significant t-value. It is to avoid non-normality issues.

Based on the aforementioned justification, PLS-SEM is deemed a more appropriate method for this study, given its variance-based approach. This analysis extends the multiple linear regression method, as PLS-SEM also estimates the coefficient that maximises the R2. PLS-SEM is considered a suitable tool to better comprehend the complexity of the research model that utilises a sufficient sample size (Hair et al., 2014; Matthews et al., 2018). The number of predictors is determined based on the largest number of indicators that form a formative construct. The PLS-SEM model comprises outer and inner models, consisting of exogenous and endogenous constructs with mediator variable constructs.

Measurement Model

The measurement model's validity and reliability will be evaluated using PLS-SEM based on the research conceptual model's type. In this research, the independent variable (green resources) and dependent variable (firm performance) are classified as Mode A reflective-formative type, whilst the mediator variable (digital technology capabilities) is categorised as a Hierarchical Component Model (HCM) of Mode B formative-formative (Type IV). The reflective model's latent construct causes the indicators, where the changes will lead to changes in the indicators. As such, the indicators are expected to be highly correlated. Green resource usage and firm performance were reflective measurements and supported by the past studies (El-Kassar and Singh, 2019; Martínez-Caro et al., 2020; Umar et al., 2022; Valase and Raut, 2019) The digital technology capabilities are formative as the indicators formed the latent constructs. As the second-order construct, the theoretical differences of the four underlying components must be maintained that resulted to capture dynamic capabilities (Pavlou and Sawy, 2011).

This assessment is suitable for models employing interval Likert scales as the measurement scale, ensuring instrument consistency (Taherdoost, 2018). After determining the appropriate model (path, reflective, or formative), researchers can proceed with the measurement model assessment (Ringle et al., 2018), as shown in Figure 3.1. Based on Ramayah et al. (2018), Cronbach's Alpha and Composite reliability tests will be utilised to evaluate internal consistency for reflective model assessment. Factor Loadings and Average Variance Extracted (AVE) will be employed to assess convergent validity, whilst the Fornell and Larcker Criterion, Cross Loadings and Heterotrait-Monotrait Ratio of Correlations (HTMT) will be used to examine discriminant validity.

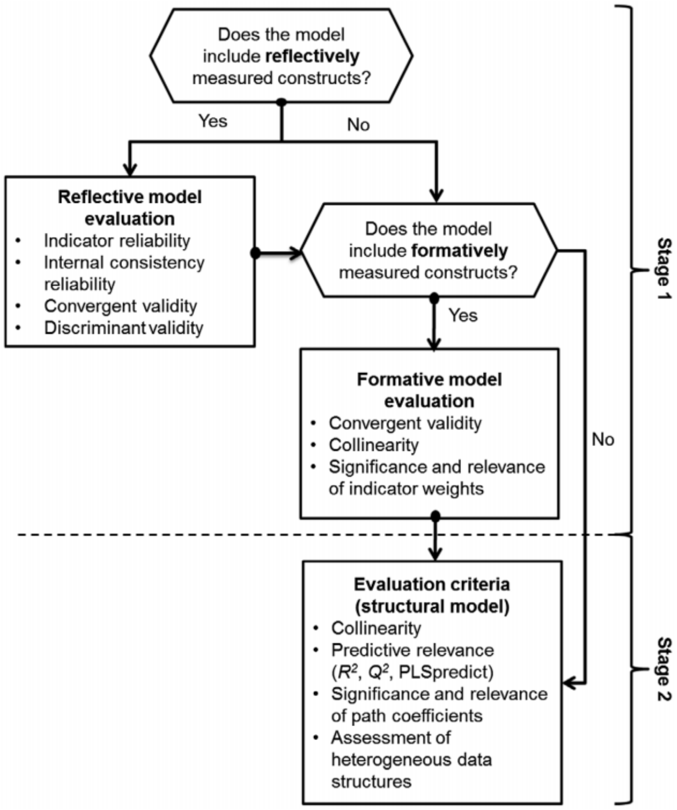


Figure 3.1: Assessment Guideline of PLS-SEM

Source: (Ringle et al., 2018)

Conversely, redundancy analysis will be employed for formative measurement models to assess convergent validity. The Variance Inflation Factor (VIF) will be utilised to evaluate collinearity issues, and outer weight significance will be used to determine the significance and relevance of formative indicators.

Reflective measurement model

For the reflective measurement model, it is advised that indicator loading values should be greater than 0.70. Items with loadings below this threshold will be removed from the model. Composite Reliability (CR), Cronbach's alpha, and rho_A will be evaluated to assess internal consistency reliability. The CR values should fall within the satisfactory to good range of 0.70 to 0.90 (Hair, Black, et al., 2019; Hair, Risher, et al., 2019). To ensure distinct causal relationships between latent variables, these values ought to be under 0.85 (Hair et al., 2019). The Average Variance Extracted (AVE) will be calculated for convergent validity, with values above 0.50 considered acceptable (Hair, Risher, et al., 2019). Discriminant validity will be further assessed by examining the Heterotrait Monotrait ratio (HTMT) and cross-loading to estimate construct correlations (Henseler et al., 2015). A recommended threshold value of 0.70 should be set to ensure that the constructed measure uniquely represents the phenomena of interest and reduces potential overlapping issues between individual indicators in a specific PLS-SEM.

Formative measurement model

The evaluation of formative measurement models encompasses convergent validity, collinearity issues, and the significance and relevance of outer weights (Hair et al., 2017). Convergent validity of formative constructs is assessed using a global reflective indicator, with a path coefficient exceeding 0.70 considered supportive. Collinearity is examined through the Variance Inflation Factor (VIF), which should be below 3 (Hair et al., 2019). This research employed a disjoint two-stage Mode B Type II, formative-formative approach (Becker et al., 2023; Hair et al., 2011; Sarstedt et al., 2019). The VIF values for the formative indicators of lower-order components were analysed. The final stage involves evaluating the significance and relevance of formative indicators. According to Hair et al. (2017b), bootstrapping results should show significant outer weights for each formative indicator; however, non-significant indicators may be retained based on content validity. Indicators must be excluded if the outer loading is below 0.5 and not significant.

Structural Model Assessment

Then, structural model assessment will be performed and consists of six steps, which are Variance Inflator Factor (VIF), path coefficient, coefficient of determination (R^2), effect size to R^2, Stone Geisser Q^2 predictive relevance and effect size of q^2 (which is optional) (Ramayah et al., 2018). The bootstrapping will be run to obtain the path coefficient. Hence, the direct effect result will determine whether to support the direct hypothesis that green resources positively affect firm performance and the role of technology capabilities. Again, digital technology capabilities have a positive effect on firm performance. Meanwhile, indirect effects will be used to determine the mediating effect of digital technology capabilities on green resources and firm performance.

Mediation Analysis Assessment

Mediation analysis assessment will be conducted using "bootstrapping the indirect effect" adopted from the Preacher and Hayes method using PLS-SEM (Hair, Black, et al., 2019; Hair et al., 2018). Full mediation can be obtained if the direct effect is not significant but the indirect effect is significant. On the other hand, partial mediation is obtained when direct and indirect effects are significant. In this study, all coefficient indicators were calculated and known as a standardised beta coefficient. Upon measuring the coefficients path, the study considers the measurement of t-statistics and p-value to determine if the developed hypothesis is significant. To accept or reject Hypothesis 1 to

Hypothesis 4, the significance level was set by 5% ($t = 1.96$) for two-tailed (Hair et al., 2017). The decision rules for each hypothesis test are set out in Table 3.8.

3.9 Chapter Summary

This chapter provided a comprehensive overview of the research methodologies employed to investigate green resource usage, digital technology capabilities, and firm performance in Malaysia's automotive industry. It outlined the research paradigm and design, detailing the quantitative approach and cross-sectional survey method. The unit of analysis was established as the automotive firm, with managerial-level respondents serving as key respondents. The chapter described the sampling frame, which includes manufacturers, assemblers, and parts suppliers, data collection procedures, measurement instruments for all constructs, and the PLS-SEM analytic approach. The subsequent chapter, Chapter 4, will focus on the data analysis and interpretation.

CHAPTER 4

DATA ANALYSIS

4.0 Introduction

This chapter discussed the analysis of the gathered data to address the research questions and hypotheses. The process begins with data screening procedures, including checks for missing data, suspicious response patterns, outliers, and normality, to ensure the accuracy and suitability of the data for further analysis. Then, an overview of respondent key was analysed, followed by descriptive and inferential statistics analysis. The PLS-SEM method was employed to assess measurement and structural analysis. The findings were presented through tables, graphs, and narrative summaries that provide a comprehensive basis for the key findings.

4.1 Response Rate and Non-response Bias

In this study, 250 questionnaires were distributed to the targeted firms. However, 190 questionnaires were received, yielding a raw response rate of 76%. Upon review, four (4) questionnaires were found incomplete, with eight questionnaires containing suspicious responses and outliers subsequently excluded from further analysis. Consequently, 178 completed questionnaires were utilised for data analysis. This resulted in a response rate of 71.2%, which is deemed good to provide a robust foundation for data analysis and interpretation of the findings

(Table 4.1). The exclusion of incomplete questionnaires due to missing or inconsistent data, along with the removal of outliers, enhances the dataset's accuracy and consistency by mitigating the risk of skewed results. This step was essential to maintain the integrity of the data analysis process.

The common response pattern was consistent with previous studies conducted in Malaysia's automotive industry concerning sustainability, innovation and firm performance studies (Habidin et al., 2018, 2015; Dawal et al., 2015; Rashid et al., 2015; Zailani et al., 2015) as well as studies on digital technology capability (Li et al., 2022a) which reported adequate response rates ranging from 22% to 57%. Although this sample size is appropriate for multivariate statistical analysis, PLS-SEM was adopted for this study (Memon et al., 2020).

Table 4.1

The Response Rate of the Questionnaire

Response	
Total questionnaires distributed	250
Questionnaires received	190
Received and usable questionnaires	178
Received and excluded questionnaires	12
Response rate percentage	76%
Usable response rate	71.2%

The method proposed by Armstrong and Overton (1977) was employed to assess non-response bias. This technique evaluates significant disparities in chosen demographic attributes between those who responded early and those who responded late to the survey. Participants were divided into two categories based on when they submitted their responses: early respondents who completed the survey by December 2023 (106 individuals) and late respondents who submitted after December 2023 (72 individuals). Independent sample T-tests were conducted to determine whether these groups had notable differences in work experience and current organisational position (Asante-Darko and Osei, 2024).

As shown in Table 4.2, the results revealed no significant variations in the two sample proportions between early and late respondents at a 5% significance level. This outcome suggests that the timing of survey completion did not affect the consistency of responses, and non-response bias did not impact the findings.

Table 4.2

Non-response bias for Demographics

	Mean Difference		Std. Deviation		Levene's Test for Equality of Variance		t-value	Sig.
	Early[a]	Late[b]	Early[a]	Late[b]	F-test	Sig.		
Current Position	2.5472	2.8611	1.36020	1.55921	2.376	0.125	-1.424	0.156
Work Experience	2.8491	2.9028	1.04008	1.15258	1.068	0.303	-0.324	0.747

[a] denotes sample size 106, and [b] denotes sample size 72

4.2 Common Method Bias Test

Common Method Bias (CMB) can influence the relationship between variables, which arises from variance in responses due to measurement methods, particularly when data is collected simultaneously using a single instrument.

Various procedures and statistical methods can be employed to identify the CMB. Podsakoff et al. (2003) implemented several recommendations during questionnaire design and administration and statistical procedures to address common method variance. These strategies included utilising diverse scale types, enhancing questionnaire clarity, guaranteeing respondent anonymity, and conducting the statistical Harman's one-factor test. The unrotated factor analysis indicated that the items accounted for over 50% of the total variance, suggesting the presence of common method bias in the study.

Regarding correlations among the principal constructs, Table 4.3 demonstrates that the highest inter-construct correlation is 0.825. However, common method bias is typically considered problematic when the correlation value exceeds 0.90 (Bagozzi et al., 1991). In conclusion, the test results indicate that common method bias is not a significant issue and can be mitigated.

Table 4.3

Correlation among Principle Constructs

Principle Constructs	**1**	**2**	**3**
1. Firm Performance	1	0.687**	0.673**
2. Green Resources	0.687**	1	0.825**
3. Digital Capabilities	0.673**	0.825**	1

Note: Correlation significant at $p < 0.01$ level

Partial Least Squares Structural Equation Modelling (PLS-SEM) was utilised as the analytical approach to examine the impacts. In particular, the Type 2 Reflective-Formative Hierarchical Component Model (HCM) was implemented. To address Common Method Bias (CMB), the Variance Inflation Factor (VIF) for the constructs was evaluated using the random variable technique proposed by Kock (2015).

4.3 Data Screening

Data screening is crucial in ensuring that research data is refined, structured, and ready for subsequent statistical analysis. This process guarantees that the data is usable, reliable, and valid for testing causal theories, highlighting how data attributes can impact future analysis and interpretation. The screening procedure involves scrutinising data for errors and making necessary adjustments prior to analysis. It commences with an examination of raw data, identification of outliers, and management of missing information. These steps align with the recommendations of Hair, Hult, Ringle, and Sarstedt (2017), who stress the importance of addressing key dataset issues. These issues include missing data, questionable response patterns (such as uniform answers and inconsistent responses), outliers, and the normality of data distribution.

4.3.1 Treatment of Missing Data

When a participant fails to answer one or more questions in a survey, either intentionally or by accident, it results in missing data. This issue must be addressed and rectified during the data preparation stage before proceeding with analysis (Hair, Black, et al., 2019b).

The study employed IBM SPSS Statistics Version 27 to conduct a missing value analysis, identifying the percentage of missing values for each variable in the dataset. According to Hair, Black, Babin, and Anderson (2019), if missing data is completely random and below 10%, it can be disregarded and retained for analysis. In this research, however, items with over 10% missing data were related to demographics of unobserved data. These variables included types of digital technologies and environmental initiatives adopted by firms, with most respondents randomly selecting three main types for each category. Consequently, additional items such as TypeDT4, TypeDT5, TypeENV4, and TypeENV5, which had more than 10% missing data, were removed. Conversely, GR14, SC03, IC05 and IC06, which had less than 10% missing data, were retained for further analysis, as illustrated in Table 4.4. The missing data for these items was deemed entirely random, and a mean substitution method was utilised to replace the missing values (Hair et al., 2017) before proceeding with additional analysis without significant bias.

Table 4.4

Summary of Missing Value Analysis

Items	Missing Data (%)
GR14	0.50
SC03	0.50
IC05	0.50
IC06	0.50
TypeDT2	4.30
TypeDT3	4.80
TypeDT4	14.0
TypeDT5	25.8
TypeENV2	2.20
TypeENV3	5.40
TypeENV4	10.8
TypeENV5	21.0

4.3.2 Suspicious Response

Subsequently, it is essential to identify a straight-lining pattern. This pattern occurs when respondents provide identical answers to numerous questions, potentially compromising the survey's validity (Hair et al., 2017). Such responses must be eliminated prior to data analysis. Standard deviation values were calculated to detect this pattern, with zero values indicating no variation in a respondent's answers across all questions. Among the 186 respondents, five questionable responses were detected and subsequently removed from the dataset, as illustrated in Table 4.5. Consequently, the remaining 181 responses were utilised for the subsequent stage of data screening.

Table 4.5

Summary of Suspicious Responses

No.Respondents	Standard Deviation (SD)
1	0.000
126	0.000
147	0.000
173	0.000
186	0.000

4.3.3 Outlier Cases

An outlier is identified when a case exhibits extreme responses across all questions (Hair et al., 2017). Whilst a univariate outlier involves an extreme value on a single variable, a multivariate outlier represents an unusual combination of scores on multiple variables (Tabachnick and Fidell, 2013). In this study, multivariate outliers were identified by calculating the Mahalanobis distance (D2) and employing a $p \leq .001$ threshold for the $\chi 2$ chi-square (Tabachnick and Fidell, 2013). The values were arranged in ascending order, and

THREE (3) response values were deemed significant outliers at D2 > χ2 = 13.815, p ≤ 0.001, d = 2, as shown in Table 4.6. These outliers were subsequently removed, leaving 178 responses for analysis.

Table 4.6

Outlier's Detection Summary

No. Respondents	D^2	p-value
6	18.60840	<0.0001
2	16.71801	<0.0001
7	14.84556	<0.0001

Note. *Sorted based on D^2 values

Table 4.6 revealed three cases that were found as major outliers in the dataset based on D^2 values. Hence, these three cases were removed from the dataset, and the remaining 178 samples were utilised in the next analysis procedures.

4.3.4 Multivariate Skewness and Kurtosis

Normal data distribution occurs when values fall within an acceptable range. For univariate analysis, the z-score of skewness should be between -2 and +2, while kurtosis should not exceed ±7 (Field, 2009; Wulandari et al., 2021). The acceptable z-score range for multivariate normality is ±3 for skewness and ±20 for kurtosis (Cain et al., 2017). As shown in Table 4.7, the majority of individual variables' z-scores for univariate skewness were within the acceptable range only for FP and GR, whereas kurtosis values were acceptable for all variables. However, multivariate statistics revealed a non-normal distribution for both skewness (4.974) and kurtosis (57.913). Mardia's multivariate normality test confirmed that the multivariate skewness and kurtosis exceeded acceptable limits, indicating a non-normal distribution.

Table 4.7

Summary of Multivariate Skewness and Kurtosis

Variables	Skewness		Kurtosis	
	Statistics	**z-score**	**Statistics**	**z-score**
Financial Performance (FP)	0.326	1.791	-0.676	-1.865
Green Resources (GR)	0.152	0.833	-0.819	-2.260
Sensing Capability (SC)	0.405	2.224	-0.666	-1.839
Learning Capability (LC)	0.451	2.475	-0.524	-1.446
Integrating Capability (IC)	0.571	3.137	-0.530	-1.464
Coordinating Capability (CC)	0.573	3.146	-0.457	-1.262
Mardia's Multivariate Normality	4.9745	147.5777	57.9138	6.749704

Note: Skewness standard error = 0.182, Kurtosis standard error = 0.362

4.4 Demographic Profile of the Respondents

Table 4.8 describes the summary of the demographic profile of respondents obtained for this study.

Table 4.8

The Key Information Regarding Respondents

	Frequency	**Percentage (%)**
Firm Size		
Less than 51	3	1.70
51-150	37	20.8
151-250	62	34.8
251-500	57	32.0
More than 500	19	10.7
Firm Year Establishment		
1-5 years	17	9.6
6-10 years	57	32.0

11-15 years	35	19.7
16 years above	69	38.8
Firm Ownership		
Local	166	93.3
Foreign	8	4.5
Others	4	2.2
Current Division		
Operational	79	44.4
Quality	33	18.5
R&D	18	10.1
Environment Health and Safety	16	9.0
IT	4	2.2
HR	28	15.7
Current Position		
Top Management	55	30.9
Managers	67	37.6
Executives	56	31.5
Work Experience		
Less than 1 year	14	7.9
1-5 years	60	33.7
6-10 years	54	30.3
11-15 years	35	19.7
16 years above	15	8.4

Note: n=178

Based on Table 4.8, the majority of participants worked in organisations with 151 to 250 employees (34.8%), with the next largest group employed by firms having 251 to 500 employees (32%). A significant portion (20.8%) was from businesses with 51 to 150 employees. Larger corporations, those exceeding 500 employees, accounted for 10.7% of respondents. The smallest representation came from companies with fewer than 51 employees, comprising only 1.7% of the sample.

Regarding the firm establishment year, the survey results indicate that the largest group of participants (38.8%) are employed by firms that have been in operation for over 16 years in the automotive industry, followed by firms operating for 6 to 10 years, accounting for 32% of respondents. Firms with 11 to 15 years of industry presence employ 19.7% of the surveyed individuals. A smaller proportion, 9.6%, work for firms that have been established for 1 to 5 years. Besides that, most of the firms are locally owned (93.3 %), followed by foreign firms (4.5 %) and others (2.2 %).

Meanwhile, in terms of job divisions, the operational division comprises the largest group at 44.4%. The Quality division follows with 18.5% of respondents, whilst the Human Resource Division accounts for 15.7%. The Research and Development (R&D) and the Environment, Health and Safety divisions each represent 10.1% and 9% of the respondents, respectively. The smallest proportion of respondents comes from the Information Technology division (2.2%). The research concentrates on top management levels, managers, and executives. As elucidated in Table 4.8, the breakdown of respondents' roles indicates that 30.9% occupy top management positions. Managers succeed in this 37.6%. While executives comprise 31.5% of respondents. In terms of work experience, the largest number of respondents (33.7%) possess 1 to 5 years of professional experience. The second-largest group (30.3%) has 6 to 10 years of experience, followed by those with 11 to 15 years (19.7%). Respondents with over 16 years of experience constitute 8.4%, while those with less than a year's experience represent 7.9%.

4.5 Descriptive Analysis of Latent Construct

The descriptive statistics for the study's latent constructs are displayed in Table 4.9. The dependent variable, Firm Performance (FP), exhibits a mean of 4.72 and a standard deviation of 1.18, suggesting moderate performance with some variation among companies.

Green Resources (GR), the independent variable, demonstrates a mean of 5.11 and a standard deviation of 0.85, indicating that the majority of firms perceive substantial use of green resources. The mediating factor, digital technology capability (DC), shows a mean of 5.14 and a standard deviation of 0.85, reflecting high digital proficiency across the organisations. This construct is composed of four latent variables: Sensing Capability (SC), Learning Capability (LC), Integrating Capability (IC), and Coordination Capability (CC). SC presents a mean of 5.20 and a standard deviation of 0.88, signifying a high level of sensing ability amongst firms. LC displays a mean of 5.13 and a standard deviation of 0.86, denoting consistent learning capacity across companies. IC exhibits a mean of 5.12 and a standard deviation of 0.90, highlighting the robust integration of digital technologies within organisations. Lastly, CC shows a mean of 5.12 and a standard deviation of 0.91, demonstrating effective coordination abilities among the firms studied.

Table 4.9

Descriptive Analysis of Latent Construct

Items	**Mean**	**Std. Deviation**
FP	4.7188	1.17804
GR	5.1116	0.84620
SC	5.2043	0.88465
LC	5.1320	0.86460
IC	5.1210	0.90191
CC	5.1180	0.91139
DC	5.1438	0.84639

Note: n =178

4.6 Measurement Model Analysis

The measurement model describes the relationship between the indicators and their relationships with the constructs, creating a path model element referred to as the outer model in PLS-SEM (Memon et al., 2021). In this study, the PLS Algorithm procedure in SmartPLS was utilised to conduct the measurement model analysis (Memon et al., 2021) Version 4.0 to evaluate construct reliability and validity. The measurement model of this study is illustrated in Figure 4.1. The model developed for this study was Mode A of the reflective-formative type and hierarchical component models (HCMs) of Mode B formative-formative (Type IV) (Becker et al., 2023; Cheah et al., 2019).

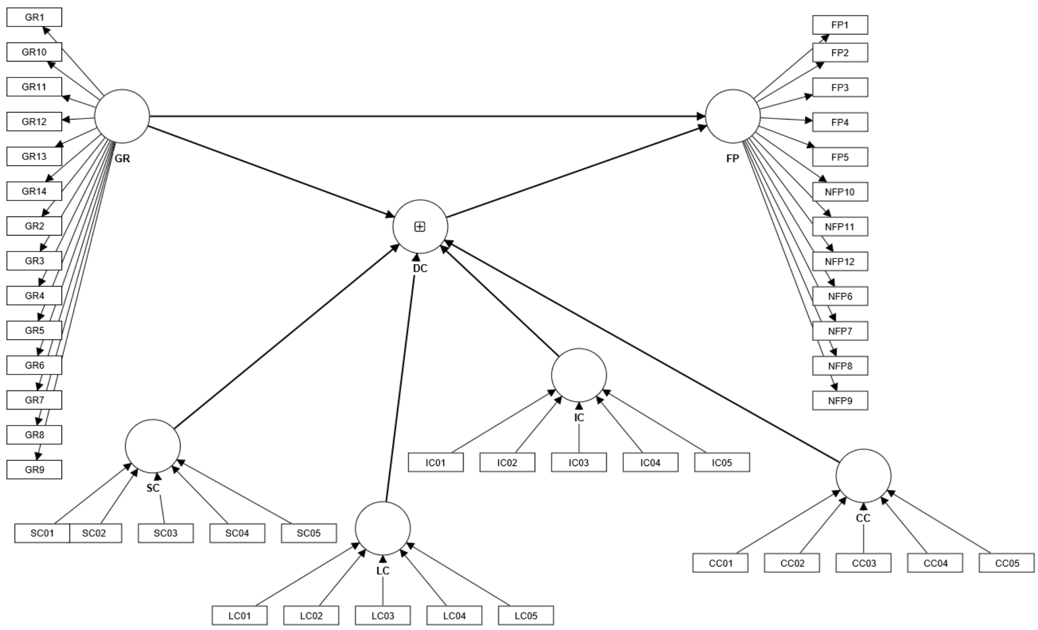


Figure 4.1
Measurement model
Note. For better visual, see Appendix III.

There are THREE (3) inner latent constructs, namely Green Resources (GR), Firm Performance (FP), and Digital Technology Capability (DC). GR and FP represent the reflective model. Meanwhile, the DC is a higher-order construct measured by FOUR (4) lower-order constructs that are formative and represented by Sensing Capability (SC), Learning Capability (LC), Integrating Capability (IC), and Coordinating Capability (CC).

4.6.1 Reflective Measurement Model

For GR and FP as reflective models, the measurement items must adequately represent the effects of latent variables. This approach, also known as Mode A in PLS-SEM (Hair et al., 2017), involves evaluating FOUR (4) aspects:

i) Internal consistency through composite reliability (ρc)
ii) Individual indicator reliability via outer loadings
iii) Convergent validity using average variance extracted (AVE)
iv) Discriminant validity assessed by the Fornell-Larcker criterion, cross-loadings, and Hetereotrait-Monotrait (HTMT) ratio

To ensure internal consistency, the composite reliability coefficient (ρc) ought to be higher than 0.7, signifying adequate convergence (Gefen et al., 2000). Moreover, the Cronbach's alpha coefficient should exceed 0.7 for all items, indicating reliability and internal coherence. Simultaneously, outer loading values surpassing 0.708 suggest that the construct effectively represents the relationship amongst indicators. Regarding convergent validity, the average variance extracted (AVE) must be greater than 0.50 (Gefen et al., 2011; Hair et al., 2017; Hair, Risher, et al., 2019). The AVE of the latent variable should be higher than its squared correlation with all other variables. As a result, no items were removed from this evaluation, and the findings presented in Tables 4.10 and 4.11 verify that each concept fulfils the specified requirements.

Table 4.10

Internal Consistency Reliability and Convergent Validity Results

Constructs	Items	Loadings	Cronbach's alpha	ρ_a	ρ_c	AVE
Firm Performance (FP)	FP01	0.907	0.983	0.983	0.985	0.841
	FP02	0.916				
	FP03	0.909				
	FP04	0.913				
	FP05	0.919				
	NFP6	0.916				
	NFP7	0.929				
	NFP8	0.934				
	NFP9	0.905				
	NFP10	0.909				
	NFP11	0.914				
	NFP12	0.934				
Green Resources (GR)	GR01	0.864	0.978	0.979	0.980	0.781
	GR02	0.900				
	GR03	0.891				
	GR04	0.868				
	GR05	0.895				
	GR06	0.893				
	GR07	0.898				
	GR08	0.872				
	GR09	0.876				
	GR10	0.871				

	GR11 GR12 GR13 GR14	0.881 0.877 0.874 0.911				

Note. None were deleted to fulfil the convergent validity requirement

Table 4.11

Results of Fornell and Larcker (1981) criterion

Constructs	FP	GR
FP	0.917	
GR	0.724	0.884

Furthermore, discriminant validity was evaluated using the Heterotrait-Monotrait (HTMT) Ratio and cross-loadings, which measures how distinct a construct is from others. The HTMT ratio represents the correlation between two constructs if they were measured flawlessly (Hair et al., 2017).

It is calculated to ensure relatively the mean of the average correlations of indicators and the mean of all indicators across different constructs measuring the same construct (Henseler et al., 2015). Cross-loadings indicate an indicator's correlation with other constructs in the model. To establish discriminant validity, an indicator's outer loading on its associated construct should exceed its cross-loadings on other constructs (Hair et al., 2017).

Table 4.12 indicates that the reflective constructs FP and GR have a ratio below 0.85 (Kline, 2016). The HTMT results suggest no issues with discriminant validity among the constructs in the measurement model. Table 4.13 shows that the outer loading values were higher than the cross-loading values, confirming the discriminant validity of the measurement model's components.

Table 4.12

Results of Hetereotrait-Monotrait (HTMT) Ratio

Constructs	CC	FP	GR	IC	LC
CC					
FP	-				
GR	-	0.735			
IC	-	-	-		
LC	-	-	-	-	

Table 4.13

Results of cross-loadings comparison

ITEMS	CC	FP	GR	IC	LC	SC
CC01	**0.985**	0.651	0.780	0.914	0.883	0.836
CC02	**0.962**	0.643	0.760	0.885	0.855	0.829
CC03	**0.938**	0.603	0.711	0.865	0.861	0.820
CC04	**0.957**	0.634	0.753	0.875	0.859	0.827
CC05	**0.936**	0.620	0.731	0.858	0.843	0.809
FP1	0.622	**0.907**	0.675	0.627	0.609	0.646
FP2	0.645	**0.916**	0.701	0.659	0.630	0.669
FP3	0.574	**0.909**	0.624	0.582	0.530	0.600

FP4	0.610	**0.913**	0.650	0.600	0.559	0.630
FP5	0.636	**0.919**	0.681	0.647	0.600	0.665
NFP6	0.576	**0.916**	0.656	0.597	0.525	0.597
NFP7	0.583	**0.929**	0.592	0.579	0.511	0.583
NFP8	0.620	**0.934**	0.679	0.644	0.573	0.643
NFP9	0.586	**0.905**	0.674	0.627	0.535	0.607
NFP10	0.622	**0.909**	0.663	0.618	0.523	0.62
NFP11	0.575	**0.914**	0.652	0.617	0.528	0.598
NFP12	0.631	**0.934**	0.701	0.658	0.581	0.674
GR1	0.684	0.701	**0.864**	0.708	0.673	0.77
GR2	0.736	0.718	**0.900**	0.733	0.693	0.782
GR3	0.705	0.644	**0.891**	0.716	0.679	0.761
GR4	0.688	0.648	**0.868**	0.708	0.643	0.734
GR5	0.758	0.656	**0.895**	0.739	0.703	0.818
GR6	0.726	0.671	**0.893**	0.739	0.702	0.804
GR7	0.707	0.596	**0.898**	0.751	0.705	0.793
GR8	0.672	0.583	**0.872**	0.718	0.676	0.749
GR9	0.640	0.564	**0.876**	0.690	0.674	0.735
GR10	0.679	0.645	**0.871**	0.712	0.683	0.755
GR11	0.688	0.630	**0.881**	0.724	0.709	0.782
GR12	0.688	0.618	**0.877**	0.719	0.699	0.749
GR13	0.640	0.600	**0.874**	0.678	0.653	0.713
GR14	0.737	0.661	**0.911**	0.755	0.697	0.800
IC01	0.881	0.670	0.806	**0.969**	0.874	0.848
IC02	0.887	0.665	0.753	**0.944**	0.847	0.819
IC03	0.893	0.634	0.741	**0.941**	0.852	0.831
IC04	0.885	0.628	0.759	**0.939**	0.849	0.824
IC05	0.872	0.619	0.757	**0.940**	0.870	0.828
LC01	0.869	0.612	0.747	0.876	**0.970**	0.858
LC02	0.868	0.605	0.755	0.876	**0.970**	0.856
LC03	0.877	0.581	0.749	0.884	**0.969**	0.860
LC04	0.855	0.557	0.737	0.865	**0.946**	0.842
LC05	0.846	0.569	0.746	0.874	**0.955**	0.860
SC01	0.818	0.640	0.839	0.839	0.869	**0.960**
SC02	0.817	0.680	0.845	0.851	0.840	**0.964**
SC03	0.813	0.653	0.848	0.838	0.838	**0.955**
SC04	0.788	0.664	0.808	0.817	0.814	**0.930**
SC05	0.809	0.658	0.781	0.821	0.822	**0.931**

Consequently, the reflective model's evaluation of measurements met the criteria for both convergent and discriminant validity. The research now progresses to the subsequent phase, which involves assessing the measurements for the formative model.

4.6.2 Formative Measurement Model

The Digital Technology Capability (DC), a Mode B formative-formative Type IV hierarchical component model (HCM) or higher-order construct, will be evaluated as a formative measurement model. In accordance with Sarstedt, Hair, Cheah, Becker, and Ringle (2019) guidelines, the higher-order construct (HOC), DC, will not be assessed as it comprises the repeated indicators: Sensing Capability (SC), Learning Capability (LC), Integrating Capability (IC), and Coordinating Capability (CC) to identify the higher-order component. These indicators solely ensure the identification of the higher-order construct and do not represent its actual measurement model.

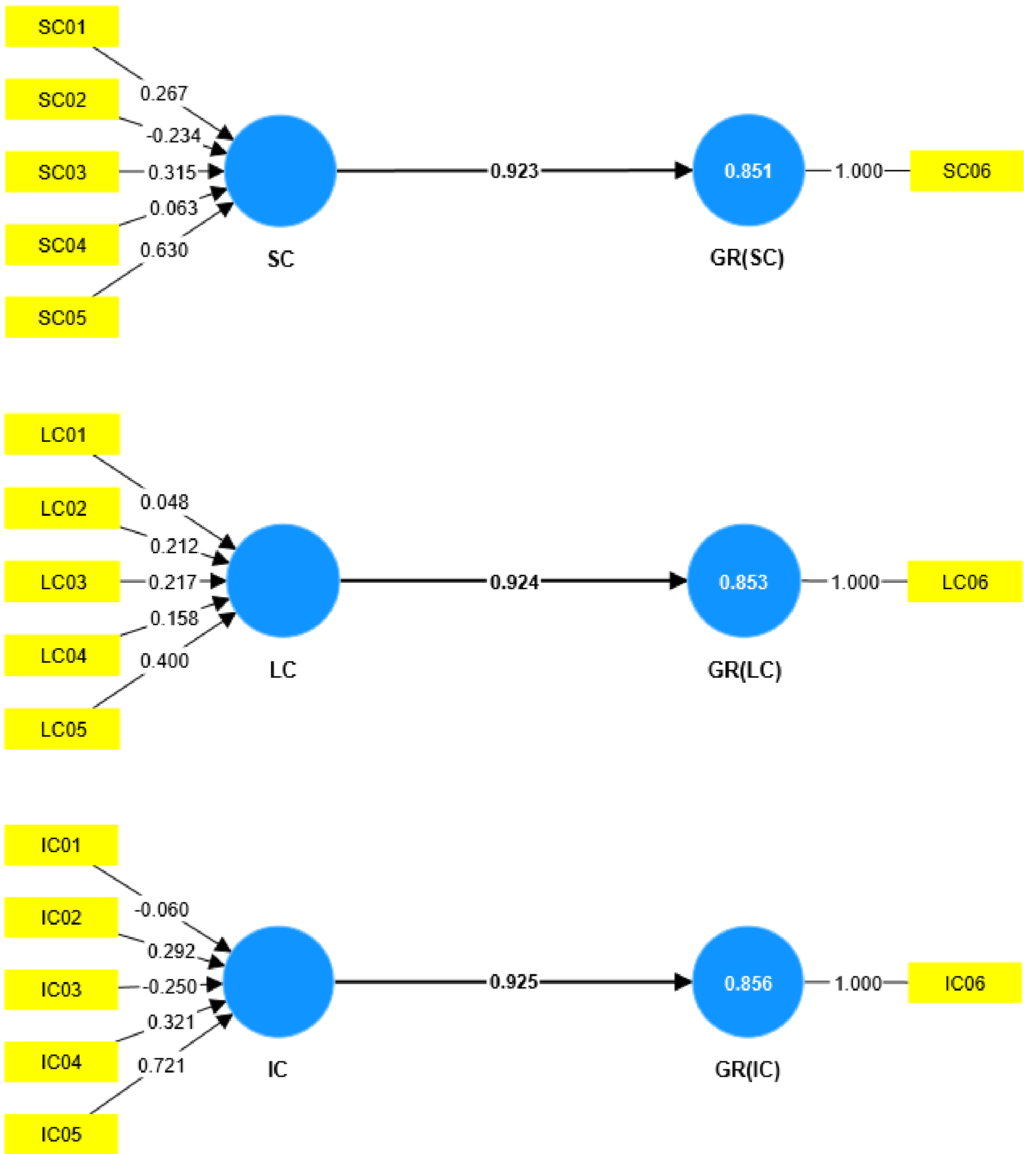
Rather, the measurement model of the higher-order construct elucidates the relationships between the higher-order component and its lower-order components (LOC). Consequently, standard measurement model assessment criteria are applied to the path relationships between higher and lower-order components. As the lower-order components constitute the higher-order component (formative-formative HCM type), weights will indicate the direction of relationships from lower-order to higher-order constructs. Thus, formative measurement models assessment (Hair et al., 2017) encompasses the following:

i) Convergent Validity

ii) Collinearity issues

iii) Significance and relevance of outer weights

Convergent validity is examined through redundancy analysis to determine if the formative measured construct correlates strongly with the reflective measured construct (Hair et al., 2017). A global reflective indicator assessed the convergence of formative constructs as shown in Figure 4.2.



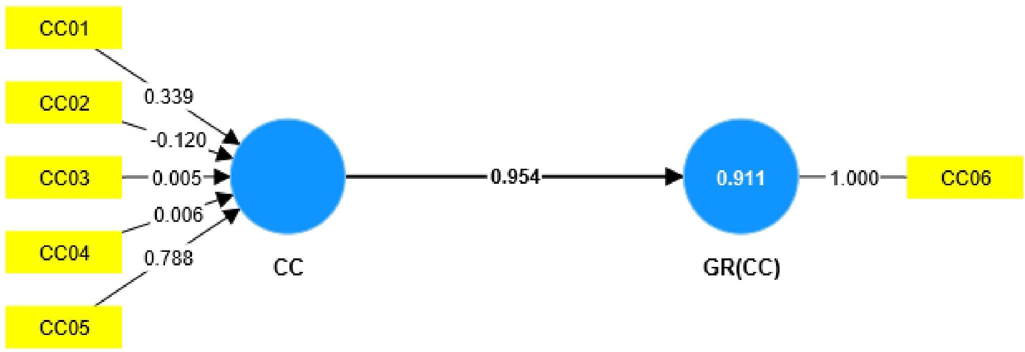


Figure 4.2
Convergent Validity for Dynamic Capabilities Components

The path coefficient must exceed the threshold of 0.70 to support convergent validity (Hair et al., 2017). Figure 4.2 outlines the redundancy analysis for lower-order components (LOC): SC, LC, IC, and CC. The analysis for the LOC components yields path coefficients above the 0.70 threshold, thereby supporting the formative construct's convergent validity.

Regarding collinearity issues, the variance inflation factor (VIF) values for the formative indicators of the lower-order components exceeded five, and the indicators' outer weights were insignificant except for SC01, SC03, IC01, and CC01, as shown in Table 4.14. However, the corresponding item loadings were above 0.50 and statistically significant. Therefore, following Hair et al. (2017), the indicators were generally retained. Given the collinearity problem among the formative LOCs, the hierarchical component model (HCM) was deemed suitable for addressing collinearity issues (Becker et al., 2023; Hair et al., 2018). This approach ensured that the estimated weights and statistical significance remained unaffected and unbiased.

The disjoint two-stage approach was employed to examine Type II errors in the formative-formative type of HCM through latent variable scores (LVS) analysis (Becker et al., 2023; Hair et al., 2011; Sarstedt et al., 2019). The VIF value for the latent variable score was below 5, which is 4.395 (Hair et al., 2011). All indicators were retained as the outer loading values were relatively high, although the outer weight values were significant except for LVS CC, as depicted in Table 4.14.

Consequently, the formative model's measurement assessment fulfilled the requirements, allowing this study to proceed to the next step, the structural model assessment for the HCM model.

Table 4.14
Results of formative measurement assessment

Construct		Items	Convergent Validity	Weights	VIF	t-value weights	p-value	Outer Loading	Decision
1st Order	**2nd Order**								
Sensing Capability	**Digital Capability**	SC01		0.119		3.192	0.001	0.920	Retained
		SC02		0.097		1.559	0.119	0.924	Retained
		SC03		0108		2.084	0.037	0.916	Retained
		SC04		0.022		0.316	0.752	0.891	Retained
		SC05	0.923	0.066	7.987	0.999	0.318	0.893	Retained
Learning Capability		LC01		0.044		0.635	0.525	0.917	Retained
		LC02		0.058		0.820	0.412	0.916	Retained
		LC03		-0.019		0.340	0.734	0.916	Retained
		LC04		0.011		0.202	0.840	0.895	Retained
		LC05	0.924	0.026	8.150	0.492	0.622	0.903	Retained
Integrating Capability		IC01		0.190		3.571	0.000	0.936	Retained
		IC02		0.007		0.147	0.883	0.911	Retained
		IC03		0.019		0.315	0.753	0.908	Retained
		IC04		-0.011		0.176	0.860	0.907	Retained
		IC05	0.925	0.083	9.641	1.465	0.143	0.908	Retained
Coordinating Capability		CC01		0.144		2.147	0.032	0.937	Retained
		CC02		0.075		1.116	0.264	0.916	Retained
		CC03		-0.088		1.285	0.199	0.892	Retained
		CC04		0.084		1.658	0.097	0.910	Retained
		CC05	0.954	0.051	7.833	0.990	0.322	0.890	Retained
	Digital Capability	LVS SC		0.780		6.663	0.000	0.977	Retained
		LVS LC		-0.367		2.578	0.010	0.870	Retained
		LVS IC		0.393		2.505	0.012	0.936	Retained
		LVS CC		0.208	4.395	1.480	0.139	0.909	Retained

Note. None of the items were deleted because the outer loading values were more than 0.50, though the outer weight values were not significant.

4.7 Structural Model Assessment

The structural model reflects the inner PLS-SEM model that elaborates on the latent variables and their path relationships (Hair et al., 2017). The structural model assessment involves five (5) systematic procedures, which include the collinearity issues, the significance of structural model relationships, the coefficient of determination, R^2, effect sizes, f^2, and predictive relevance, Q^2.

This study adopted HCM using the disjoint two-stage approach, as shown in Figure 4.3. The latent variable scores of LOC were utilised to measure the higher-order construct in assessing the structural model.

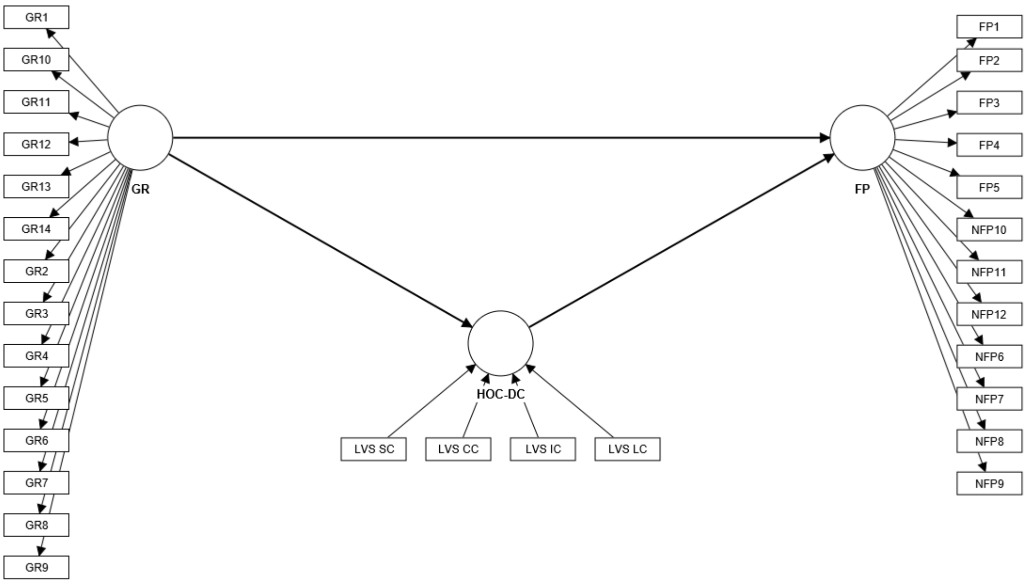


Figure 4.3
Structural model: HCM Model of Disjoint Two-Stage Approach
Note. For better visual, see Appendix III.

4.7.1 Collinearity Assessment

Multi-collinearity is a statistical fact describing how two or more independent variables are highly correlated in a multiple regression model (Bougie and Sekaran, 2019). Hair et al. (2017) posited that the variance inflation factor (VIF) quantifies the severity of collinearity among the indicators in a structural model. However, the HOC model was employed to assess the full collinearity issue in this study. A common method bias was conducted by introducing a random variable for examination. The tolerance value VIF of the predictor constructs was below 3.3, as presented in Table 4.15, indicating an absence of pathological collinearity and freedom from common method bias (Kock, 2015).

Table 4.15

Variance Inflation Factor values -Common Method Bias

Latent Variables	**Collinearity (VIF)**			
	HOC-DC	FP	GR	Random
HOC-DC				1.020
FP				2.131
GR				2.102
Random				

Table 4.16 presents the collinearity statistics for predictor constructs. The VIF values for HOC-DC to FP were 4.395, GR to HOC-DC is 1.00 and GR to FP is 4.395. The VIF values were below 3.3 (Diamantopoulos and Siguaw, 2006) and 5.0 (Hair et al., 2011). Consequently, this structural model effectively mitigates collinearity issues and ensures that the results produced are not misleading (Sarstedt et al., 2019). Therefore, the higher-order component (HOC) model was utilised for the remaining structural assessments.

Table 4.16

Variance Inflation Factor values -Inner model for Latent Variables Score

Latent Variables	**Collinearity (VIF)**		
	HOC-DC	FP	GR
HOC- DC		4.395	
GR	1.000	4.395	

4.7.2 Explanatory Power and Effect Sizes

The R^2 model's explanatory power is also known as the coefficient of determination (Ramayah et al., 2018). It quantifies the proportion of an endogenous construct's variance explained by its predictor constructs in the structural model. Through structural model path relationships, higher R^2 values indicate a better explanation of the construct by the latent variables in the structural model. Generally, R^2 values of 0.25, 0.50, and 0.75 are considered weak, moderate, and substantial, respectively (Hair et al., 2017). Figure 4.4 demonstrates that the Firm Performance (FP) exhibits a moderate level of explanatory power (R^2= 0.551), indicating that Green Resources (GR) and the higher-order component Digital Technology Capability (HOC-DC) account for approximately 55.10% of the variance in FP. Similarly, the HOC-DC demonstrates substantial explanatory power (R^2= 0.772). This value suggests that GR accounts for 77.2% of the variance in HOC-DC.

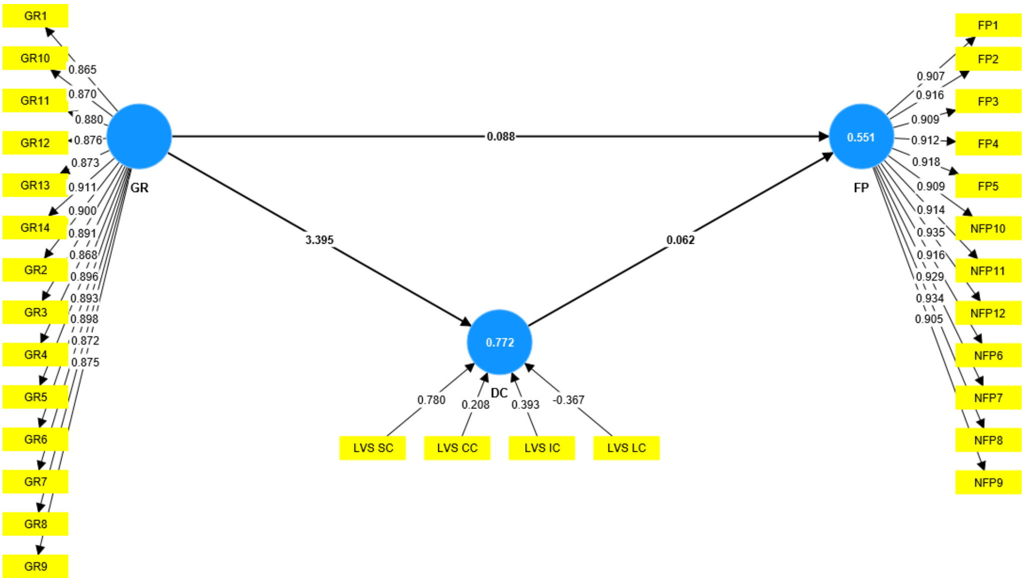


Figure 4.4

Main Effect Model: Explanatory Power

Note: Values on the arrow indicate f^2. The value within the endogenous construct represents R^2.

Conversely, the f^2 effect size is utilised to evaluate a predictor construct's relative impact on an endogenous construct (Hair et al., 2017; Hair, Black et al., 2019). The effect size refers to the variation in the R^2 value that assesses the extent of changes in the R^2 when a deleted predictor variable is present and its substantive impact on the dependent variable.

According to Hair et al. (2019), Jacob Cohen's guideline determines the effect size magnitudes. The effect sizes of small, medium, and large are represented, respectively, as 0.02, 0.15, and 0.35. Table 4.17 indicates that GR (f^2=0.088) and HOC-DC (f^2=0.062) exhibit small effect sizes (f^2) on FP. Although these variables, GR and HOC-DC, demonstrate a small effect, their contribution may still be significant in this study and may elucidate subtle influences on FP. In contrast, GR (f^2=3.395) exhibits a large effect on HOC-DC, which may elucidate the significance of green resource usage through the mediating role of digital technology capabilities in influencing firm performance.

Table 4.17

Results of computed effect sizes (f^2) and variance explained (R^2)

Relationships	Effect Size (f^2)	Magnitude	Variance Explained (R^2)
H1: GR -> FP	0.088	Small	0.551
H2: GR -> HOC-DC	3.395	Large	0.772
H3: HOC-DC -> FP	0.062	Small	

4.7.3 Predictive relevance, Q^2

Additionally, predictive power was measured in Q^2. It examines whether a model accurately predicts data not utilised to estimate model parameters. This PLS-Predict measures out-of-sample predictive power (Hair et al., 2017; Hair, Black, et al., 2019; Shmueli et al., 2019). Based on Hair et al. (2019), the Q^2 values are considered small if $Q^2 > 0$, medium is 0.25, and large is 0.50, as a rule of thumb.

Furthermore, according to Shmueli et al. (2019), when interpreting PLS predict results, one should:

i) focus on the model's key endogenous construct (i.e., dependent variable)
ii) need to evaluate Q^2_predict to verify and ensure that the predictions outperform the most naïve benchmark (i.e., Q^2_predict > 0)
iii) examine the prediction statistics. In most instances, use the RMSE, but if the prediction error distribution is highly non-symmetric, the MAE is more appropriate
iv) compared to the RMSE (or MAE) values with a naïve benchmark.

Consequently, Table 4.18 demonstrated that all manifest variables of endogenous constructs in the model have Q^2 values above zero (i.e., ranging from 0.340 to 0.750), supporting the reputation model's predictive relevance for three endogenous constructs (Hair, Black, et al., 2019). The PLS-SEM RMSE values are less than the LM RMSE values, indicating they are significant except for item FP3 (1.036) and NFP11 (1.051). Thus, this structural model exhibits a medium out-of-sample predictive power, implying that most PLS-SEM RMSE values are lower than the LM RMSE values.

Table 4.18

Results of PLS-Predict

Items	**PLS-SEM**		**LM**
	Q^2 predict	**RMSE**	**RMSE**
LVS CC	0.614	0.642	0.656
LVS IC	0.659	0.587	0.630
LVS LC	0.591	0.643	0.703
LVS SC	0.750	0.503	0.540
FP1	0.451	1.010	1.027
FP2	0.485	0.967	0.997
FP3	0.384	1.036	1.027
FP4	0.416	1.021	1.051
FP5	0.458	1.012	1.043
NFP10	0.437	1.023	1.056
NFP11	0.422	1.051	1.049
NFP12	0.486	0.984	0.990
NFP6	0.425	1.002	1.025
NFP7	0.340	1.075	1.105
NFP8	0.458	1.023	1.039
NFP9	0.452	0.996	1.017

Note. LM = Linear regression Model, RMSE = Root Mean Square Error

Regarding the latent construct, Table 4.19 demonstrated that predictive values are positive and exceed zero, indicating predictive power within the inner model at the structural level. This suggests that the model can effectively predict the data. Consequently, there is no absolute error in MAE or RMSE. This means that HOC-DC shows a strong predictive relevance (Q^2 predict = 0.761) with lower prediction error (RMSE = 0.500, MAE = 0.371), indicating highly accurate predictions. In contrast, FP has moderate predictive relevance (Q^2 predict = 0.521) but with higher prediction errors (RMSE = 0.701, MAE = 0.551), reflecting relatively less accurate predictions compared to HOC-DC.

Table 4.19

Results of PLS-Predict for Latent

Items	**PLS-SEM**		
	$Q^2_{predict}$	**RMSE**	**MAE**
HOC-DC	0.761	0.500	0.371
FP	0.521	0.701	0.551

Note. RMSE = Root Mean Square Error MAE = Mean absolute error

4.7.4 Significant Testing

Structural model analysis, or significance testing, is the process of testing whether a certain result is likely to occur by chance. It involves testing whether a path coefficient differs from zero in the population. Typically, test the probability of a pattern, such as a relationship between two variables occurring by chance alone, to see if the null hypothesis is true (Saunders et al., 2016). Statistical inference is the process of concluding about the population based on data describing the sample drawn from that population. Such a test does not allow the researcher to infer that the findings are of substantive importance. Thus, significance testing of structural model relationships involves assessing basic measures such as path coefficient (β), the empirical *t*-values (*t*-statistics), probability value (*p*-value) (Hair, Black, et al., 2019; Hair et al., 2018, 2017; Hair, Risher, et al., 2019) and confidence interval (Hahn and Ang, 2017).

The empirical t-value is the statistic obtained from the data set for determining a coefficient's significance, while the critical *t*-value is the benchmark. The null hypothesis of no effect will be rejected if the empirical *t*-value is larger than the critical *t*-value. The benchmarks that are commonly used for critical *t*-values for one-tailed tests are 1.28, 1.65, and 2.33. Meanwhile, p-values are $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. For this study, the significance level was set at 5% ($t = 1.65$) for the one-tailed test. The result was reviewed as unsupported if the p-value exceeded the significance level.

Next, the path coefficient represents a structural model's estimated path relationship between latent variables. It is also identical to a regression model's standardised beta (β) values. Kock and Hadaya (2018) asserted that hypothesised relationships might not be significant if β values range from 0 to 0.10 and if β values exceeding 0.20 are more likely to indicate the occurrence of a significant relationship. Meanwhile, it is unable to determine the significance of the hypothesised relationship if the values are between 0.11 and 0.19.

Similarly, confidence interval values are provided as accuracy measures for the p-value to enhance the reporting of significance testing. The threshold of p-values ($p < 0.10$, $p < 0.05$, and $p < 0.01$) provides a general benchmark for researchers to accept or reject the null hypothesis (Aguinis et al., 2017). Consequently, the confidence interval demonstrates the proximity of the lower and upper bound limits to the zero point, summarising as a component of rigorous results reporting in quantitative studies (Hahn Ang, 2017; Ramayah et al., 2018). Therefore, the value of the confidence interval upper limit (UL) and lower limit (LL) must be both positive or negative and not within the range of upper and lower bound values (Hair et al., 2017). Employing bootstrap distributions of 10,000 subsamples for this analysis will mitigate estimated random variations, enabling the sample to represent the population more accurately (Becker et al., 2023).

Table 4.20 presents the results in the structural model of direct relationships obtained in this study. The path coefficient indicates that the usage of green resource, GR, is positively significant in influencing digital technology capabilities, HOC-DC (β =0.879, t = 38.384, p < 0.001, LL =0.830, UL = 0.919) and firm performance, FP (β =0.724, t = 17.717, p < 0.001, LL =0.636, UL =0.796). However, GR exhibits the most substantial effect on HOC-DC (0.879) compared to FP (0.724). Additionally, HOC-DC significantly and positively influences FP (β = 0.348, t = 3.104, p < 0.002, LL = 0.150, UL = 0.591) with an effect of 0.348. The direct effect path relationships between green resources and firm performance, green resources and digital technology capabilities, and digital technology capabilities and firm performance are significant at the 5% level. Hence, the results support the hypotheses H1, H2, and H3. The result indicates that the use of green resources (GR) positively influences the enhancement of automotive firm performance. Furthermore, the use of green resources positively influences the role of digital technology capabilities (HOC-DC) in the organisation. Similarly, the role of digital technology capabilities also significantly improves automotive firms' performance (FP).

Table 4.20

Results of significance testing (direct relationship)

Relationships	*β*	T statistics	*p* values	Confidence Interval		Result
				LL	UL	
H1: GR -> FP	0.724	17.717	<0.000*	0.636	0.796	Supported
H2: GR -> HOC-DC	0.879	38.384	<0.000*	0.830	0.919	Supported
H3: HOC-DC -> FP	0.348	3.104	0.002*	0.150	0.591	Supported

Note. One-tailed test, $t = 1.65$, $P < 0.05$*

4.7.5 Mediation Effect

Additionally, several methods exist to assess the mediation effect or indirect association, such as bootstrapping the indirect impact, i) Baron and Kenny's causal procedure method, and ii) the Sobel assessment (Ramayah et al., 2018). However, Preacher and Hayes (2004) method of indirect effect bootstrapping was adopted in this study, which was further supported by Preacher and Hayes's (2008). The method was employed for several reasons:

i) The causal process method developed by Baron and Kenny has been criticised for having inferior statistical power and for leading researchers to incorrectly conclude that a mediation effect is present when none exists (Rungtusanatham et al., 2014).

ii) This study has a non-normal data distribution. Thus, the Sobel test is inappropriate, particularly in a study with non-normal data. The result will be in lower statistical power than other options because the distributional assumptions will not hold for the indirect effect.

Moreover, the percentile bootstrap approach was utilised to test the mediation effects to obtain bias-corrected confidence interval estimates (MacKinnon et al., 2004). The bootstrap approach can address non-normal data distribution issues (Preacher and Hayes, 2004; Zhao et al., 2010). This study identified the different forms of mediation to further extract outcomes from the mediation analysis (Hair et al., 2017; Nitzl et al., 2016). However, before determining the forms of mediation, the mediating impact (a x b) must be significant. According to MacKinnon, Fairchild, and Fritz (2007), three forms of mediation exist: complete, competitive partial, and complementary partial mediation.

Zhao, Lynch Jr, and Chen (2010) and Nitzl, Roldan and Cepeda (2016) further elucidated the types of mediation. Full mediation occurs when the indirect effect is significant, and the direct effect is not substantial. Competitive partial mediation indicates that indirect and direct effects are significant and operate in opposite directions, either positive or negative. On the other hand, when indirect and direct effects are significant and operate in the same direction, either positively or negatively, complementary partial mediation occurs.

Tables 4.21 and 4.22 demonstrate that GR -> HOC-DC -> FP is supported, with HOC-DC exhibiting significant indirect effects on GR and FP ($\beta = 0.306$, $t = 3.024$, $p = 0.003$, LL = 0.130, UL = 0.527). Consequently, the results support hypothesis H4. This study reveals that both the direct effect of GR -> FP (β =0.724, $t = 17.717$, $p < 0.001$, LL =0.636, UL =0.796) and the indirect effect of GR -> HOC-DC -> FP ($\beta = 0.306$, $t = 3.024$, $p = 0.003$) are significantly positive. Therefore, an examination of mediation types is necessary to determine the relationship for GR -> HOC-DC -> FP (H3). Both the direct effect GR -> FP (β

=0.724, t = 17.717, p < 0.001, LL =0.636, UL =0.796) and the indirect effect GR -> HOC-DC -> FP (β = 0.306, t = 3.024, p = 0.003) are significantly positive.

As Ramayah, Cheah, Chuah, Ting and Memon (2018) proposed, Variance Accounted For (VAF) is required to determine the type of mediation. Based on Nitzl, Roldan and Cepeda (2016), the VAF is computed using the following formula:

VAF = [Coefficient of Indirect effect / (Coefficient of Indirect effect + Coefficient of Direct effect)] x 100

VAF = [0.306/ (0.306 + 0.724)] x 100

= 29.709 %

The calculated VAF value of 29.709% falls between 20% and 80%, indicating a complementary partial mediation effect (Nitzl et al., 2016). Thus, the results confirm that this study categorises H3: GR -> HOC-DC -> FP as a complementary partial mediation effect. This finding suggests that digital technology capabilities partially elucidate the impact of green resources on firm performance.

Table 4.21

Results of significance testing (mediating relationships)

Relationships	***β***	**T statistics**	***p* values**	**Confidence Interval**		**Result**
				LL	**UL**	
H4: GR -> HOC-DC-> FP	0.306	3.024	0.003*	0.109	0.502	Supported

Note. One-tailed test, t = 1.65, P < 0.05*, Bias Corrected.

Table 4.22

Results of significance testing (mediating relationships)

Relationships	*β*	T statistics	*p* values	Type of Mediation
H4: GR -> HOC-DC-> FP	0.306	3.024	0.003*	Complementary (Partial Mediation)

Note. One-tailed test, t = 1.65, P < 0.05*, Bias Corrected.

4.8 Summary of Type of Digital Technologies, Type of Environmental Initiatives and Challenges in Digital Technology Adoption

4.8.1 Type of Digital Technologies

Participants were requested to specify the digital technologies implemented by their organisations. The findings indicated that these technologies could be categorised into three main functions, as shown in Table 4.23. The primary motivation for firms adopting digital technologies was centred on Data, Connectivity, and Computation (n=240). These technologies were instrumental in improving connectivity, data gathering, and information processing to facilitate data-driven decision-making (I. Lee and Lee, 2015; D. Lin et al., 2018; Maksimovic, 2018; Syafrudin et al., 2018; Xu et al., 2018).

The Internet of Things (IoT), Big Data and Analytics, and Cloud Computing were among this category's most widely adopted technologies. The smooth integration between systems and devices would streamline operations across various company divisions. The second function of digital technologies pertained to Automation, Intelligence, and Smart Systems (n=179). This aspect focused on the automotive sector utilising enablers to support the transition towards smart manufacturing or smart factories (Araujo et al., 2021; Arcidiacono et al., 2022; Hamdi et al., 2019; Kahveci et al., 2022; H. Lee et al., 2022; T.-C. Lin et al., 2020). Cyber-Physical Systems, Simulation and Autonomous Robots, System Integration, and Artificial Intelligence were among the tools adopted for this purpose. These technologies ensure system integration and enable intelligent decision-making, thereby enhancing productivity and achieving operational efficiency that improves company performance.

Finally, digital technologies play a crucial role in enhancing manufacturing processes, particularly in relation to Manufacturing, Visualisation, and Materials (n=93) (Araujo et al., 2021; Dawal et al., 2015; Haleem and Javaid, 2019; Kong et al., 2016; C.-H. Lee et al., 2021; Mourtzis et al., 2022; Rahamaddulla et al., 2021; Vacchi et al., 2021). Companies acknowledged the significance of these digital technologies in optimising production processes from raw material handling to the final product. Additive Manufacturing, Advanced Materials, and Augmented Reality were commonly adopted tools that could enhance the innovation process and product quality.

Table 4.23

Type of Digital Technologies Adoption

Type of Digital Technologies	Frequency
Data, Connectivity, and Computation	**240**
Internet of Things	143
Big Data and Analytics	79
Cloud Computing	18
Automation, Intelligence, and Smart Systems	**179**

Cyber-Physical Systems	92
Artificial Intelligence	15
Simulation and Autonomous Robots	40
System Integration	32
Manufacturing, Visualization, and Materials	**93**
Additive Manufacturing	71
Advanced Materials	15
Augmented Reality	7

Note: n=178 (Respondent select more than ONE(1) adoption)

4.8.2 Type of Environmental Initiatives

Within the realm of sustainable practices, participants were requested to categorise the environmental initiatives adopted by their organisations. These initiatives were divided into FIVE (5) distinct groups, as illustrated in Table 4.24. The categories comprised Resource Optimisation and Waste Minimisation, Sustainable Resource Use, Environmental Impact Reduction, Comprehensive Environmental Management, and Other Sustainable Practices. Amongst these classifications, the firms' primary focus was associated with Environmental Impact Reduction (n=192) (Ahmed et al., 2014; Fernando and Hor, 2017; Ismail and Zaidi, 2017; X. Li and Nam, 2022a, 2022b; Zhang et al., 2023).

The use of Life Cycle Assessment (LCA) was essential for the firms to assess the environmental impact associated with the life cycle of automotive products for improvement and decision-making. At the same time, firms also focused on emission reduction, reflecting their awareness and commitment to decreasing greenhouse gas emissions. Besides that, Comprehensive Environmental

Management (n=148) was equally important to the firms (Dawal et al., 2015; Fuzi et al., 2018; Habidin et al., 2016). The adoption of an environmental management system helped firms effectively manage their environmental impact and improve their overall performance.

Following closely were Resource Optimisation and Waste Minimisation (n=124). The firm emphasises efficient resource use and minimising waste during the production process to foster sustainability (Fernando and Hor, 2017; Ghobakhloo and Fathi, 2020; Giampieri et al., 2020a, 2020b; Mohamad-Ali, Ghazilla, Abdul-Rashid, et al., 2017a; Narula et al., 2023; Shahbazi et al., 2018; Shin et al., 2018; Shukor et al., 2017; Varela et al., 2019; Wen Chiet et al., 2019; Zainuddin et al., 2019). The firm also practised Sustainable Resource Use (n=44), focusing on managing water consumption and product recovery (Babel et al., 2020; Gohoungodji et al., 2020; Jasiński et al., 2016; Kasava et al., 2020; Mohamad-Ali, Ghazilla, Abdul-Rashid, et al., 2017b). Lastly, some firms also adopted other sustainable practices (n=4). These demonstrate that the automotive industry firms are committed to long-term sustainability through the reduction of resource consumption.

Table 4.24

Type of Environmental Initiatives

Types of Environmental Initiatives	Frequency
Resource Optimisation and Waste minimisation	**124**
Lean Production	98
Material Efficiency	26

Sustainable Resource Use	**44**
Water Management	34
Product Recovery	10
Environmental Impact Reduction	**192**
Life Cycle Assessment (LCA)	114
Emission Reduction	78
Comprehensive Environmental Management	**148**
Environmental Management Systems	148
Others Sustainable Practices	4

Note: n=178 (Respondent select more than ONE (1) adoption)

4.8.3 Challenges in Digital Technology Adoption

The automotive sector continues to grapple with the implementation of digital technologies. Table 4.25 illustrates the ranking of these obstacles, from most to least significant, as reported by survey participants. The primary hurdle identified was insufficient funding (44.4%) (Borovkov et al., 2021; Herceg et al., 2020), which respondents cited as a significant impediment to embracing digital technology. Issues such as obsolete manufacturing methods, the absence of strategic planning, and the intricacy of incorporating digital technologies could hamper production efficiency. The second most pressing challenge was a dearth of information (24.2%) (Borovkov et al., 2021; Chauhan et al., 2021). Ineffective information dissemination within organisations can decelerate the adoption process and hinder decision-making.

The third obstacle was a shortage of skilled personnel (23%) (Borovkov et al., 2021; Herceg et al., 2020). A lack of specialists with requisite qualifications and practical experience can impede the integration of digital technologies. This was followed by standardisation issues (33.3%) (Borovkov et al., 2021; Chauhan et al., 2021; Herceg et al., 2020). Inconsistent implementation of standards and processes across various management tiers may cause resistance to change, particularly at lower levels, thus delaying the uptake of digital technologies. Lastly, the fifth challenge was cybersecurity (47.8%) (Borovkov et al., 2021; Chauhan et al., 2021). Ensuring secure access via digital channels and safeguarding the privacy and security of organisational data remained significant hurdles for companies.

Table 4.25

Challenges in Digital Technologies Adoption

Challenges in Digital Technologies Adoption	**Frequency**	**Percent (%)**
First Challenges		
Lack of Finance	**79**	**44.4**
Lack of Information	6	3.4
Lack qualified employee	57	32.0
Research and Education Costs	17	9.6
Cyber Security	13	7.3
Standardisation problem	6	3.4
Second Challenges		
Lack of Information	**43**	**24.2**
Research and Education Costs	41	23.0
Standardisation problem	35	19.7
Lack of Finance	24	13.5
Lack qualified employee	19	10.7
Cyber Security	16	9.0
Third Challenges		
Lack qualified employee	**41**	**23.0**
Lack of Finance	35	19.7
Standardisation problem	36	20.2
Research and Education Costs	34	19.1
Lack of Information	18	10.1

Cyber Security	14	7.9
Fourth Challenges		
Standardisation problem	**70**	**39.3**
Lack of Information	55	30.9
Cyber Security	23	12.9
Lack of Finance	13	7.3
Lack qualified employee	12	6.7
Research and Education Costs	5	2.8
Fifth Challenges		
Cyber Security	**85**	**47.8**
Lack of Finance	20	11.2
Lack qualified employee	19	10.7
Standardisation problem	19	10.7
Research and Education Costs	19	10.7
Lack of Information	16	9.0

Note: n=178 (Respondent ranks the options)

4.9 Chapter Summary

This chapter presented the findings of the empirical investigation into green resource usage, digital technology capabilities, and firm performance within Malaysia's automotive industry. The data screening process ensured the absence of missing values, outliers, and common method bias in the dataset employed for this investigation. The measurement model analysis subsequently validated the reliability and validity of all examined constructs. A comprehensive table was presented, encapsulating the key information of the target respondents and the background details of their respective firms. Furthermore, the chapter elucidated the coefficients, t-statistics, and p-values for each hypothesised relationship, testing H1 to H4. The ensuing chapter, Chapter 5, will expound upon the findings, elucidate their implications, address the study's limitations, and propose recommendations for future research endeavours.

CHAPTER 5

DISCUSSIONS AND CONCLUSION

5.0 Introduction

This chapter commences with a recapitulation of the study's purpose, theoretical framework, and methodology, synthesising how the research addressed the objectives, examining green resource usage, digital technology capabilities, and firm performance in Malaysia's automotive industry. The discussion of findings interprets the results for each hypothesis linked to the RBV and DCV. The research implications are presented, and research limitations are acknowledged. The chapter concludes with recommendations for future research.

5.1 Recapitulation of the Study

This study aims to analyse the impact of green resource usage and the role of digital technology capabilities on the automotive industry in Malaysia. Hence, this study summarised statistical analysis, descriptive analysis, and hypothesis testing.

5.1.1 Statistical Analysis Summary

From a total of 250 distributed questionnaires, 178 were processed and analysed using SmartPLS 4.0 software. A comprehensive description and analysis of the respondents' information and firms were conducted to enhance interpretation.

The research model's reliability and validity were examined, and the research hypotheses were analysed through the application of the PLS-SEM methodology.

5.1.2 Descriptive Analysis

According to respondents, most automotive firms implement environmental impact reduction strategies, followed by comprehensive environmental management, resource optimisation, and waste minimisation as environmental strategies within their organisations. Specifically, these firms in the industry focus primarily on environmental management systems, life cycle assessment, lean production, and emission reduction. Material efficiency, water management, and product recovery are the least implemented initiatives.

Regarding digital technology adoption, automotive firms predominantly focus on data, connectivity, and computation tools, followed by automation, intelligence, and smart systems tools, as well as manufacturing, visualisation, and materials-related tools. Specifically, most automotive firms have adopted the Internet of Things (IoT), Cyber-Physical Systems, Big Data and Analytics, Additive Manufacturing, and Simulation and Autonomous Robot technologies. System integration, cloud computing, artificial intelligence, advanced materials, and augmented reality are the least adopted technologies. In terms of challenges, automotive firms in the industry primarily face a lack of finance, information, qualified employees, standardisation problems, and cyber security issues, all of which are in descending order of prevalence. When these challenges were ranked by frequency, cyber security and lack of finance scored the highest, followed by standardisation problems, lack of information, and lack of qualified employees.

5.1.3 Hypothesis Testing Summary

In this study, Table 5.1 presents a summary of the results of the hypothesis testing. All hypotheses were supported. The direct effect and indirect effect were significant and positive. Given that both effects are significant and exhibit the same directionality, the study confirms that digital technology capabilities partially mediate the relationship between green resources and firm performance.

Table 5.1
Summary of the results of the Hypothesis Testing

No	Hypotheses	Decision Rule	**Result**
1	H1: Green resource usage positively influences the performance of automotive firms.	Decision Rule: Accept H1 if the p-value <0.05* H1 was supported	Significant (p-value= <0.001)
2	H2: Green resource usage positively influences the digital technology capabilities of automotive firms	Decision Rule: Accept H2 if the p-value <0.05* H2 was supported	Significant (p-value= <0.001)
3	H3: Digital technology capabilities positively influence the performance of automotive firms.	Decision Rule: Accept H3 if the p-value <0.05* H3 was supported	Significant (p-value= 0.002)
4	H4: Digital technology capabilities mediate the relationship between green resource usage and automotive firm performance.	Decision Rule: Accept H4 if the p-value <0.05* H4 was supported	Significant (p-value= 0.003) (complementary)

Note: t = 1.65, P < 0.05*

5.2 Discussion of Findings

The findings of this study are thoroughly examined in the discussion section.

5.2.1 Effects of Green Resources Usage on Automotive Industry Firms' Performance

The research question, objectives, and hypothesis pertaining to green resources and automotive industry firms' performance are presented herein.

RQ: Does green resource usage affect the firm performance in Malaysia's automotive industry?

RO: To investigate the effects of green resource usage on automotive firm performance.

H1: Green resource usage positively influences the performance of automotive firms.

The positive effect of green resources (GR) on automotive firm performance (FP) ($\beta = 0.724$, $p < 0.000$) highlights the importance of green resource usage in enhancing firm performance to achieve competitive advantage. The causal relationship is supported by the theoretical grounding of the RBV. Automotive firms that effectively use VRIN green resources are positioned better to meet stakeholder expectations and improve performance to be competitive and sustained in the industry. The result supports the idea that most of the firms in the industry are keen on eco-friendly manufacturing processes to enhance operational efficiency and move towards a low-carbon automotive sector Madrid, 2023). The implementation of green practices articulates the firm's internal strategies in utilising green resources efficiently and effectively to leverage firm performance (Latifi et al., 2021). The concurred

Transitioning toward smart factories and building green facilities enables firms to reduce costs and carbon emissions efficiently. Concentrating on the innovation of green products and processes, particularly developing and promoting electric vehicles (EVs), is aligned with the government roadmap to achieve sustainability goals. Introducing lightweight vehicles and using recyclable materials eventually improves fuel efficiency and resource optimisation, and reduces emissions. This study concurred with the Alos-Simo et al. (2020) study that eco-innovation activity positively contributes to firm revenue. This is consistent with a study by Abdul Ghafar and Mohd Razali (2022) that green practices in the Malaysian automotive sector enhance financial and operational performance. The study results contradicted with Nureen et al. (2023) that the green manufacturing practices do not affect firm performance. This action complies with environmental standards and appeals to environmentally conscious consumers to drive market growth, where institutional support may encourage green resource consumption. Consequently, the small effect size demonstrated green resource usage may have stronger effects on operational performance than financial performance, resulting in enhancing firm performance, particularly in Malaysia, as an emerging market where green differentiation remains uncertain. The growing consumer demand enhances firms' revenue growth, improves profit margins, attracts investors and financing and is dynamic in changing markets.

The findings supported the previous studies on Malaysian manufacturing firms in the automotive industry, which strongly adopt green practices and have significantly contributed to enhancing financial and operational performance (Abdul Ghafar and Mohd Razali, 2022; Maldonado-Guzmán et al., 2023; Mohamad-Ali et al., 2024). Past findings merely examined green practices and strategies and were sparse on resources specifically. The findings of this research added value as it emphasises the utilisation of green resources. Past findings by Kasava et al. (2020) descriptively revealed that 90.9% of Malaysia's automotive firms agreed that resource utilisation was one of the most important factors that applied sustainable manufacturing principles.

Indeed, green resource utilisation represents a small effect size ($f^2 < 0.15$) and explains a substantial portion of the variance ($R^2 = 0.551$) that significantly provides a more potent influencer for firm performance ($\beta = 0.724$). Thus, Malaysian automotive firms are keen on improving resource efficiency by optimising green resource usage. The automotive industry is a major contributor to carbon emissions, and firms are increasingly focusing on minimising resource consumption for sustainability and cost-effectiveness. The green resource showcases the industry firms' determination to reduce emissions and commitment to achieving net-zero greenhouse gas (GHG) emissions by 2030 and underscores the positive impact of circular economy principles on resource management. These findings provide evidence that Malaysian automotive firms are using lightweight steel, recycled materials, remanufacturing, recycling battery materials, and reducing raw material dependency. These activities improved operational efficiency and enhanced financial performance through cost savings. As such, the industry begins to give attention to the need for recycling, remanufacturing and end-of-life recovery practices in a more holistic approach to mitigate and achieve net-zero carbon emission (Madrid, 2023).

5.2.2 Effects of Green Resources on the Role of Digital Technology Capabilities of Automotive Firms.

The research question, objectives, and hypothesis regarding green resources and the role of digital technology capabilities are presented herein.

RQ: Does green resource usage affect the role of digital technology capabilities?
RO: To investigate the effects of green resource usage on the role of digital technology capabilities of automotive firms.
H2: Green resource usage positively influences the digital technology capabilities of automotive firms

Green resources (GR) exert a significant and strong influence on digital technology capabilities (DC) ($\beta = 0.879$, $p < 0.000$), explaining a substantial proportion of its variance ($R^2 = 0.772$). This finding supports the idea that using green resources with strong digital technology capabilities optimises sustainability initiatives, improves resource efficiency, and complies with environmental regulations. The relationship between green resources and digital technology capabilities is key to how sustainability initiatives drive digital technological transformation within firms. The relationship in the Malaysian automotive industry reflects how these firms utilise digital tools to optimise green resource usage and improve resource efficiency.

Using green resources such as renewable resources, waste resources, energy, water, and human capital, along with more sophisticated digital technologies, improves firms' internal capabilities and maximises their effectiveness and efficiency in resource management. The result is consistent with the study by Khan et al. (2022) that adopting Industry Revolution 4.0 tools will influence the circular economy by using natural resources efficiently, reducing waste production, and enhancing remanufacturing. Moreover, these heavily resource-dependent automotive firms face external pressures to be sustainable to gain a competitive advantage and refuse to lag behind their competitor (Szász et al., 2021). Hence, adopting digital technologies is essential to utilising efficient resources in the automotive industry. Yadav et al. (2020) concurred that despite a firm adopting green resources, monitoring sustainable activities through digital technology capabilities is mandatory to penetrate sustainability effectively.

Additionally, consistent with previous studies, firms that leverage digital technologies like the Internet of Things (IoT), big data analytics, Cyber-Physical Systems (CPS), Additive manufacturing, Advanced robotics, and Advanced Manufacturing Technologies can monitor and optimise the resource usage and reduce emissions (Bonnard et al., 2021; Calış Duman and Akdemir, 2021; Khan et al., 2021; Singh and El-Kassar, 2019). The green resources also foster innovation, which relies heavily on digitally driven products, whereas the automotive sector includes creating electric vehicles, autonomous vehicles, and connected car technologies. As these digital technologies support innovation, these firms integrate green resources to create environmentally friendly vehicles that enhance functionality and performance. Creating digital infrastructure for green innovation enhanced the firm's decision-making and strategic planning. Integrating digital technologies enhances the firms' internal capabilities in forecasting their operations' environmental impacts, assessing their products' life cycle, and making data-driven decisions that support.

Contrarily, this study contradicts Gohoungodji et al. (2020), discussed that most firms face financial challenges in implementing green initiatives within the industry. Besides, circular economy practices in the Malaysian automotive sector are hindered due to a lack of awareness and a shortage of expertise (Yahaya et al., 2024). The incidence would occur if the resources were not utilised efficiently, increasing the cost to the firm and leading to financial losses. The optimisation of resources by using digital technologies enhances the capabilities of automotive firms and improves decision-making at the managerial level, specifically strategic, tactical, and operational levels, to be more dynamic and sustainable (Bag et al., 2020). This study proved that Malaysian automotive firms are resourceful in investing in green practices to maximise green resource usage by leveraging internal digital technology capabilities. Malaysian automotive firms are overcoming these barriers, which may reflect due to government support. The organisation of automotive firms supports internal change by practising sustainability and maximising green resource usage, which contributes to leveraging digital technology capability. Automotive firms enable technology transfer and green practices' know-how, and learning processes occur within an organisation with the assistance of digital technology. The processes support enhancing green resource utilisation and contribute to operational efficiency and enhancing firm performance to position the firms for long-term success in an increasingly eco-conscious and technology-driven market.

5.2.3 Effects of Digital Technology Capabilities on Automotive Industry Firms' Performance.

The research question, objectives, and hypothesis regarding digital technology capabilities and firm performance are presented herein.

RQ: Do digital technology capabilities affect firm performance in Malaysia's automotive industry?

RO: To examine the effects of digital technology capabilities on automotive firm performance.

H3: Digital technology capabilities positively influence the performance of automotive firms.

Digital technology capabilities (DC) positively impact firm performance (FP) ($\beta = 0.348$, $p = 0.002$), which highlights the important role of digital technologies in influencing firm performance. Although the effect size of digital technology capabilities on firm performance is smaller than that of green resources (GR), it nonetheless emphasises the growing importance of digital technologies in improving firm performance. Adopting and effectively utilising digital technologies enables Malaysian automotive firms to streamline their production operations, enhance decision-making processes and offer innovative products that improve financial and operational performance. These findings are consistent with previous findings indicating that digital technologies positively improve firm performance (Calış Duman and Akdemir, 2021; Gillani et al., 2020) and supported by Bag et al. (2021) and Y. Li et al. (2020) that digital technologies enhance the firm's capability to improve operational performance. On the other hand, Syed (2023) study in Malaysia's automotive industry echoed that digital technology capabilities significantly minimise waste in the industrial processes that affect firm performance.

The Malaysian automotive firms that have augmented their digital technology capabilities are able to increase profitability, value, efficiency, competitiveness, turnover, and market share and decrease operational costs (Varela et al., 2019). However, this finding contradicts Li et al. (2022) study that digital capabilities among chinese manufacturing have an insignificant direct relationship with firm performance, but an indirect significant influence on firm performance. The results may explain that the maturity stage of Malaysian automotive firms is in earlier stages compared to Chinese manufacturing that more digitally advanced.

In this case, fully leveraging digital technology capabilities enhances the firm's agility in improving products to address customer needs and gain a competitive advantage during uncertainty. The phenomenon could reflect the recent scenario in the Malaysian automotive industry context, as firms are progressing extensively towards the Industrial Revolution 4.0. Though the adoption of digital technology is still at an early stage in Malaysia (Adnan et al., 2023), automotive firms acknowledged the need to adopt digital technologies and build internal capabilities as demand towards EEV and next-generation vehicles is increasing to achieve zero carbon manufacturing (Syed, 2023). Thus, the automotive industry must adopt and integrate different digital technologies to remain competitive and minimise the operational cost that influences firm performance (Lei et al., 2023).

According to a study by Belhadi et al. (2020), implementing a smart manufacturing system significantly improves firms' overall performance in India. The small, medium, and micro enterprises benefited from minimising costs, improving time and quality, optimising production, and enhancing flexibility. The advantages will only be fruitful if smart manufacturing systems are integrated internally to respond to dynamic changes. Li et al. (2020) asserted similar results that implementing digital technologies influences a firm's performance. Past studies agreed that building the dynamic capabilities of digital technologies enables the integration and coordination of front-end and back-end technologies to enhance the firm performance (Bag et al., 2020, 2021; Y. Li et al., 2020).

However, this study demonstrated that the effect size of digital technology capabilities among automotive firms on firm performance was relatively smaller yet impactful. The results demonstrate that automotive firms might not have entirely been driven to embrace and assimilate digital technologies into their manufacturing processes and product development, though implemented due to an urge for external factors such as consumer preferences, market trends, and governmental regulations. Large firms are usually ready and fast to initiate digital technologies more smoothly than smaller and medium-sized firms (Y. Li et al., 2020). On the other hand, adoption and leveraging one or fewer digital technologies may slow the diffusion of gaining full potential benefits that influence firm performance (Lei et al., 2023). The incurred cost for adoption and the lack of technical knowledge are additional drivers contributing to slow diffusion (Azman and Ahmad, 2023). This development testifies to automotive firms that practice sustainability approaches, adopt digital technologies and leverage their internal capabilities by sensing the opportunities, learning, integrating, and coordinating green resources to improve their financial and operational performance.

5.2.4 Digital Technology Capabilities as the Mediator between Green Resources and Automotive Industry Firms' Performance.

The research question, objectives, and hypothesis regarding digital technology capabilities as the mediator between green resources and firm performance are presented here.

RQ: Do digital technology capabilities mediate the relationship between green resources and automotive firm performance?

RO: To examine the mediating effects of digital technology capabilities on the relationship between green resource usage and automotive firm performance.

H4: Digital technology capabilities mediate the relationship between green resource usage and automotive firm performance.

The mediation analysis revealed that digital technology capabilities mediate the relationship between green resource usage and firm performance ($\beta = 0.306$, $p = 0.003$), suggesting a complementary mediation. The findings imply that green resources directly affect firm performance, and the relationships are amplified indirectly by the positive impact of digital technology capabilities. In other words, green resources not only contribute directly to improving the firm performance of the automotive industry but also strengthen the relationship by fostering the development of digital technology capabilities, which enhances the performance of automotive firms financially and operationally. The synergy between green resources and digital technology capabilities in this research context leads to greater firm performance.

This study corroborates past research findings on how green practices with digital technology capabilities enhance environmental and firm performance (Belhadi et al., 2020; Li et al., 2020; El-Kassar and Singh, 2019; Beier et al., 2018). However, limited studies have proven that digital technology capabilities mediate between green resources and firm performance. This finding added value in terms of knowledge and empirical. Previous findings focus on green practices as mediators between digital technologies and sustainability performance (Bag et al., 2021; Umar et al., 2022) and digital technology capabilities as mediators in investigating the implementation of Industrial Revolution 4.0 technologies on firm performance (Bag et al., 2020; Li et al., 2022). Moreover, prior Southeast Asian studies, Setiawan et al., (2025), have a similar direction, in which digital technology mediates the relationship between green innovation and business performance among automotive firms in

Indonesia. Additionally, relevant literature from Vietnam has focused on digital capabilities as a moderator (Trần et al., 2025) and the integration synergy between the circular economy and Industry 4.0 (Mai et al., 2026). Consequently, this study provides a novel perspective by introducing digital technology capabilities as a mediator to explain how a firm efficiently utilises green resources to enhance firm performance, specifically in the Malaysian automotive manufacturing industry. Thus, fills geographical distinct and theoretical gaps, providing empirical evidence that digital capabilities serve as the activation mechanism for undeveloped green resource value (Khan et al., 2026)

The results align with the past findings from Chauhan et al. (2021), who suggest that a firm requires a digital roadmap to build internal capabilities and utilise the resources to create sustainable firm performance. Although digital technologies improve firm performance, intrinsic barriers negatively moderate the relationship with firm performance. For instance, the barriers include coordination problems, competence issues, lack of digital strategy, absence of an adequate management system, and data integration challenges. Indeed, what matters is not the quantity of digital technologies adopted but the quality of digital technology capabilities fostered at a firm level.

More noteworthy, the greater the implementation of front-end technologies (smart manufacturing, smart supply chain, smart working and smart product) integrated with base technologies (IoT, Big Data Analytics, Augmented reality, Cloud, etc.) enhances the visibility and real-time access that develops firm's capabilities resulting in improving firm performance (Bag et al., 2020; Umar et al., 2022). For instance, automotive firms introduce eco-friendly vehicles and use AI-driven tools to monitor emissions and energy usage. Integrating digital tools enables automotive firms to track energy usage, optimise vehicle servicing, and improve operational efficiency. Dynamic digital technology capabilities require firms to choose the right resources to create a competitive advantage, leading to better firm performance.

This study's results support that the dimensions of dynamic digital technology capabilities, sensing, learning, integrating, and coordinating, partially mediate utilising green resources to improve firm performance. The finding implies that automotive firms with strong digital technology capabilities are more likely to leverage their green resources effectively to improve firm performance and achieve greater competitive advantage. The findings support the idea that automotive firms are very observant in fulfilling customer needs and learn to do better, quicker, and more efficiently by integrating green resources to improve synchronisation and coordination within the firm when combined with digital technology capabilities to enhance performance.

This study proves the synergy effect of green resources and digital technology capabilities to drive better firm performance and not operate in isolation. The finding is that Malaysian automotive firms are determined to move towards net zero carbon emissions and potentially contribute to a circular economy approach (Valladares Montemayor and Chanda, 2023). To face uncertainty and be dynamically ready, green practices equipped with unique green resources combined with inner-built digital technology capabilities can handle the complexities of the modern market to remain sustainable and competitive.

5.3 Research Implications

5.3.1 Theoretical Implications

The findings of this study provide evident contributions to RBV and DC theories in several ways.

Within the framework of the RBV, green resources are demonstrated to be valuable, rare, inimitable, and non-substitutable resources (Barney et al., 2001), particularly for automotive firms in the industry. In this study, green resources include tangible, intangible and people-based resources. The finding elucidates that Malaysian automotive firms utilise green resources knowledgeably to enhance firm performance.

A broader perspective of green practices and resource utilisation was merely centered, along with barriers to the circular economy (Abdul Ghafar & Mohd Razali, 2022; Kasava et al., 2020; Maldonado-Guzmán et al., 2023; Yahaya et al., 2024). These findings uphold the perspective of how automotive firms in Malaysia practice green strategies by utilising green resources in the production process to improve firm performance driven by external environmental pressures. The external pressure on minimising and neutralising carbon emissions is seen as the main driving force for using green resources in industrial processes.

However, as the Industrial Revolution changed over time, merely possessing green resources did not guarantee influencing firm performance. There was a growing demand to renew ordinary resources to be dynamically competitive. From the perspective of DC views, digital technology capabilities are essential to leverage green resource optimisation and efficiently drive firm performance. Digital technology capabilities act as “game changers”, enabling automotive firms to advance the industry by efficiently sensing the opportunity, learning, integrating, and coordinating green resources (Pavlou and Sawy, 2011; Warner and Wäger, 2019).

The findings confirm that green resources significantly influence the development of digital technology capabilities, which enhances firm performance. The effect size highlights the strong relationship between green resources and digital technology capabilities. Thus, this study shows that automotive firms are potent and mature in leveraging green resources to drive performance. This study aligned with the seminal work of RBV, which states the heterogeneity and immobility of green resources and the necessity of digital-enabled dynamic capabilities to improve firm performance. Digital technology capabilities closed the loop between green resource optimisation and firm performance. This study extends the RBV-DCV framework to an emerging economy context and provides solid evidence highlighting the importance of fostering digital technology capabilities rather than merely adopting digital technologies. The findings proved the readiness of Malaysian automotive firms to build digital technology capabilities tailored to their organisation's strengths to leverage green resources and improve firm performance. Thus, this study details the underlying mechanisms through which digital technology capabilities can be best utilised across the automotive industry (Bhatti et al., 2022).

Furthermore, the finding demonstrated that digital technology capabilities partially mediate the relationship between green resource usage and firm performance. This study edifies that green resources are vital in influencing performance in automotive firms. The impact is significantly amplified when integrated with digital technology capabilities to enhance and improve firm performance, financially and operationally, where regulatory framework and institutional support create unique boundary conditions. By synergising green resources and digital technology capabilities, automotive firms are more likely to achieve superior financial and operational performance (Matarazzo et al., 2021).

5.3.2 Practical Implications

Regarding managerial implications, the results suggest a few contributions to automotive firms.

Moving towards zero net carbon emissions and addressing consumer pressure (Maldonado-Guzmán et al., 2023), automotive firms diligently practice green strategies to improve firm performance. Prioritising the efficient use of green resources has become a focal point for product and production processes. The findings of this study support Malaysia's national policies (National Automotive Policy (NAP) 2020, the National Energy Transition Roadmap (NETR), and Low Carbon Mobility Blueprint) by demonstrating that green resource usage positively influences firm performance. This study elaborated that resource-efficient practices are economically beneficial, creating a business phenomenon that aligns with environmental goals.

However, merely achieving normal performance levels will not suffice for the firm to remain long-term. Instead, automotive firms must continuously invest in research and development (R&D) to maximise utilisation or replace existing green resources with innovative and eco-friendly resources (Savastano et al., 2022). This aligns with the National Energy Transition Roadmap (NETR), which emphasises technological innovation and adopting renewable energy sources to achieve net-zero carbon emissions. Managers should constantly audit current resource consumption and identify substitution opportunities. Digital technologies help monitor and optimise the use of green resources in industrial processes. Relevant study by Chen et al., (2025) demonstrated AI-enabled resource allocation will improve manufacturing efficiency. The data obtained will be helpful for automotive firms in planning resource allocation strategically, minimising the overuse of raw materials, exploring remanufacturing and recycling, and planning end-of-life recovery. Additionally, Wu et al., (2025) found robotic automation in circular manufacturing reduces virgin material. Through this, we can see an evolution of the circular economy approach, such as end-of-life recovery, remanufacturing, and recycling of resources that can improve firm performance. In the end, long-term policies on circular economy strategies that support end-of-life (ELV) legislation could be proposed and implemented to formalise recycling and remanufacturing. Automotive firms that optimise the use of green resources contribute towards the circular economy approach and should be included while providing appropriate feedback to policymakers.

Additionally, the strong green resources and digital technology capabilities relationship and mediation finding indicate that green resources and digital capabilities are complementary. Managers should avoid siloed investment and instead proactively plan and secure institutional funding to adopt and leverage digital technologies, integrating green strategies. The manager should consider expanding AI-driven predictive analytics for resource forecasting. This echoes the call in the National Energy Transition Roadmap (NETR) for greater public-private collaboration to drive technological transformation. Wong and Kee (2022) emphasised that financial and technological support from the government or institutions plays a critical role in reducing the financial burden of technological transformation. Thus, the inducement of digital technology adoption among Small and Medium Enterprises through grants and technical assistance can leverage digital technologies. The action will result in automotive firms improving speed, agility, and operational efficiency, which aligns with the Automotive National Policy (NAP, 2020) objectives to foster innovation and competitiveness within the sector.

Managers must focus on analysing, assessing, and updating the analytical information into valuable insights to drive the market (Li et al., 2022). This involves building an agile operational framework that responds to market demands and minimises operational costs. Digital technology capabilities enable firms to sense and explore new opportunities, learn by doing, and integrate resources to optimise business coordination. The information is essential for managers in the decision-making process to improve operational agility by utilising enabled digital technologies. Moreover, recent evidence demonstrated that digital twins enable the reduction of resource waste (Kankanamge et al., 2026). To achieve these outcomes, managers take strategic actions to cultivate an organisational culture that improves collaboration and coordination between departments within firms. Thus, promoting AI and digital twin adoption are vital through Industry Revolution 4.0. This approach is consistent with national digital transformation efforts, such as the 12th Malaysia Plan and National Energy Transition Roadmap (NETR), to ensure that firms can capitalise on government initiatives to accelerate technological adoption. Investing in cutting-edge technologies and digital infrastructure will position firms to lead in a competitive global market.

To effectively leverage digital technologies, firms must build a skilled workforce capable of assimilating and implementing these technologies at the department level. Training personnel in AI, IoT, and data analytics for green resource management is important to enhance digital-green technical expertise. Lack of skilled and technical expertise is identified primarily reason for circular economy barriers (Yahaya et al., 2024). Hence, developing talent aligns with the Automotive National Policy’s focus on upskilling human capital to meet the demand of Industry 4.0. A holistic view should be adopted to evaluate the firm’s strengths and weaknesses to craft a comprehensive strategy to enhance digital technology's capabilities. Managers must adopt a forward-thinking approach, emphasising continuous learning and innovation. Fostering an organisational culture that supports sensing market trends, learning, and integrating resources for optimal coordination will enable firms to adapt to environmental changes and maintain long-term sustainability.

5.4 Research Limitations

Notwithstanding, this study significantly contributes to the body of knowledge and is not without limitations. Although the questionnaire items were validated, the high Cronbach's alpha values are acknowledged as a methodological limitation, and future research should refine the measurement instruments. In terms of the scope of the study, the research primarily focuses on automotive firms already engaged in green practices and adopting digital technologies. While the study provides valuable insights into the sectoral behavioural utilisation of green resources and digital technology capabilities and their impact on firm performance, it excludes certain manufacturers across Malaysia. The automotive industry is a major contributor to carbon emissions and resource consumption, the insights may not fully apply to other sectors. This might restrict the broader capture of the actual maturity of green practices and digital technology capabilities overall in Malaysia.

Furthermore, this study examined the relationships between green resources, digital technology capabilities and firm performance through the Resource Based View (RBV) and Dynamic Capabilities (DC) theoretical lenses. Using the quantitative research method, the findings provide robust evidence of how these factors influence firm performance. However, the findings require an in-depth exploration of the role of green resources and digital technology capabilities in improving firm performance. Exploring the synergistic effects of green resources and digital technology capabilities on firm performance, particularly in the automotive sector would help uncover additional knowledge and practical implications.

5.5 Recommendations for Future Research

Based on the limitations of this study, several avenues for future research are recommended to deepen and broaden the understanding of the relationship between green resources, the role of digital technology capabilities, and firm performance.

Addressing the high Cronbach's alpha limitation requires refining the measurement instruments. In the future, the redundant items need to be identified and reduced, and testing alternative conceptualisations. Besides, future studies are recommended to expand this study to other Malaysian sectors, such as electrical and electronics (E&E), palm oil, and food processing, to investigate the sub-industry's behaviour. Different industries exhibit distinct characteristics regarding green resource utilisation, digital technology capabilities, and firm performance. Exploring sectoral variation could reveal unique challenges and opportunities in leveraging green resources and digital technology capabilities, offering valuable insights into industry-specific strategies for sustainable and technological advancement.

While this study highlights the findings merely from quantitative methods, future researchers should explore qualitative to examine the synergistic effects further.

Specifically, the interplay between green resources and digital technology capabilities affects firm performance. The more diverse the research strategies adopted to achieve the same results, the higher the validity of these research findings.

Additionally, future research may examine the role of external factors, such as government regulations, stakeholder pressure, and market competition, in mediating the relationship between green resources, digital technology capabilities, and firm performance. The role of firms' size, respondents' race, and gender in moderating this relationship may also be explored. Investigating how these external factors or specific firm characteristics influence or enhance the relationship would provide valuable insights for academia and practitioners.

Lastly, while the study focused on firm performance, future research should examine other critical outcomes, such as environmental and social impact. These dimensions will provide a holistic view of sustainable performance that could benefit from green resource usage and digital technology capabilities.

5.6 Chapter Summary

The study investigated the relationship between green resource usage, the role of digital technology capabilities, and firm performance in the context of automotive firms. This study employed a quantitative approach. The results supported H1, H2, H3 and H4. H1 demonstrated a significant positive effect of green resources on automotive firm performance. H2 observed a significant positive relationship between green resources and digital technology capabilities. H3 revealed that digital technology capabilities significantly positively affect firm performance. H4 confirmed the complementary mediating role of digital technology capabilities in the relationship between green resource usage and firm performance.

This study makes several necessary contributions to the body of knowledge. It provides empirical evidence of the significance of green resource usage and the roles of digital technology capabilities in driving firm performance. It also extends the theoretical understanding of the Resource-Based View (RBV) and Dynamic Capabilities (DC) by corroborating the integration of green resources with advanced digital technologies to achieve greater performance outcomes. As well, highlights the mediating role of digital technology capabilities in offering insights into the synergistic effects of linking sustainability practices with technology advancements. These results will help, theoretically and practically, to create better environments for automotive firms to facilitate the usage of green resources to enhance digital technology capabilities and improve firm performance.

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APPENDIX I: QUESTIONNAIRE

Dear valued respondents,

I am currently pursuing a Doctor of Philosophy at University Tunku Abdul Rahman, Kampar campus, Perak. My research topic is entitled "**Green Resources, Digital Capabilities, And Firm Performance: Evidence From Malaysia's Automotive Industry**". Your responses to this survey will be invaluable in achieving the research objectives. All responses will be anonymous and kept **CONFIDENTIAL**. The findings will be used for academic purposes only.

This study aims to have better insight into the impact of green resource usage and the role of digital technology capabilities on the automotive industry performance in Malaysia.

I am grateful if you could spare about 10-15 minutes of your valuable time. Your kind cooperation is very much appreciated. If you have any enquiries, please do hesitate to email me at anna.arokianathen@1utar.my.

Thank you for your time and co-operation.

Yours sincerely,

Anna Arokia Nathen

Faculty Business and Finance
University Tunku Abdul Rahman

By submitting or providing your personal data in this study, it is deemed that you have consented and agreed for your personal data to be used in this study. Your data will be processed and protected in accordance with the provision of the Personal Data Protection Act 2010.

I understand that my participation is voluntary, and I am free at any time to withdraw from the study without giving any reasons. I understand that the information obtained from this study will help in achieving the objectives of this study. I give my consent to participate in this survey.

Yes ☐ No ☐

Section A: Firm Performance

Please mark your answer within 1 to 7. The scale range is from **Strongly Disagree (VSD)** to **Strongly Agree (VSA)**. Your response will be kept confidential.

Firm Performance (Financial)								
No	**Currently, our firm ………**	**Strongly Disagree**	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
FP1	Achieved the targeted profit growth.	1	2	3	4	5	6	7
FP2	Achieved the targeted sales growth.	1	2	3	4	5	6	7
FP3	Achieved the targeted return on investment.	1	2	3	4	5	6	7
FP4	Achieved the targeted market shares.	1	2	3	4	5	6	7
FP5	Overall financial performance improved	1	2	3	4	5	6	7

Firm Performance (Non-Financial)								
No	**Currently, our firm ………**	**Strongly Disagree**	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
NFP 6	Improved the product quality.	1	2	3	4	5	6	7
NFP 7	Improved in operational cost reduction.	1	2	3	4	5	6	7
NFP 8	Improved the speed of production process.	1	2	3	4	5	6	7
NFP 9	Improve wastage reduction	1	2	3	4	5	6	7
NFP 10	Improve energy usage	1	2	3	4	5	6	7
NFP 11	Improve the competitiveness of business	1	2	3	4	5	6	7
NFP 12	Overall non-financial performance improved	1	2	3	4	5	6	7

Section B: Green Resources

Please mark your answer within 1 to 7. The scale range is from **Strongly Disagree (VSD)** to **Strongly Agree (VSA)**. Your response will be kept confidential.

Green Resources								
No	**Questions** **Our Firm……….**	**Strongly Disagree**	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
GR1	uses environmentally friendly resources.	1	2	3	4	5	6	7
GR2	uses renewable resources.	1	2	3	4	5	6	7
GR3	uses reusable parts.	1	2	3	4	5	6	7
GR4	recycle the waste.	1	2	3	4	5	6	7
GR5	saves the use of energy.	1	2	3	4	5	6	7
GR6	saves the use of water.	1	2	3	4	5	6	7
GR7	uses technology in the production operation processes to reduce pollution and emission.	1	2	3	4	5	6	7
GR8	uses technology to save energy, water, and waste.	1	2	3	4	5	6	7
GR9	invest in R&D projects to achieve environmentally friendly operations.	1	2	3	4	5	6	7
GR10	have well skilled workers to achieve resource efficiency.	1	2	3	4	5	6	7
GR11	have well experienced workers to achieve resource efficiency.	1	2	3	4	5	6	7
GR12	have well skilled workers in developing green products and processes.	1	2	3	4	5	6	7
GR13	have well experienced workers in developing green	1	2	3	4	5	6	7

	products and processes.							
GR14	Overall, our firm improved resource efficiency.	1	2	3	4	5	6	7

Section C: Role of Digital Technologies Capability

Please mark your answer within 1 to 7. The scale range is from **Strongly Disagree (VSD)** to **Strongly Agree (VSA)**. Your response will be kept confidential.

Role of Digital Technologies Capabilities (Sensing)								
No	**Questions** **The adoption of digital technologies enables us to…….**	**Strongly Disagree**	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
SC01	Frequently scan environment to identify opportunities.	1	2	3	4	5	6	7
SC02	Periodically review the likely effect of the customers.	1	2	3	4	5	6	7
SC03	Review products development efforts	1	2	3	4	5	6	7
SC04	Detect changes in customers' preferences	1	2	3	4	5	6	7
SC05	Observe customers' needs.	1	2	3	4	5	6	7
SC06	Improved overall sensing capabilities.	1	2	3	4	5	6	7

Role of Digital Technologies Capabilities (Learning)								
No	**Questions** **The adoption of digital technologies enables us to…….**	**Strongly Disagree**	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**

LC01	Have effective routines to identify new information and knowledge.	1	2	3	4	5	6	7
LC02	Have effective routines to value new information and knowledge.	1	2	3	4	5	6	7
LC03	Have adequate routines to assimilate new information and knowledge.	1	2	3	4	5	6	7
LC04	Effective in using knowledge into value creation (new product and process)	1	2	3	4	5	6	7
LC05	Effective in developing new knowledge	1	2	3	4	5	6	7
LC06	Improved overall learning capabilities.	1	2	3	4	5	6	7

Role of Digital Technologies Capabilities (Integrating)								
No	**Questions** **The adoption of digital technologies enables us to…….**	**Strongly Disagree**	**Disagree**	**Somewhat**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
IC01	Contribute individual input to the firm.	1	2	3	4	5	6	7
IC02	Integrate with the new information and knowledge acquired	1	2	3	4	5	6	7
IC03	Integrated information in the firm	1	2	3	4	5	6	7
IC04	Have effective communication between individuals.	1	2	3	4	5	6	7
IC05	Being aware of who in the firm has specialized skills and knowledge.	1	2	3	4	5	6	7
IC06	Improved overall integrating capabilities.	1	2	3	4	5	6	7

Role of Digital Technologies Capabilities (Coordinating)								
No	**Questions** **The adoption of digital technologies enables us to…….**	**Strongly Disagree**	**Disagree**	**Somewhat**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
CC01	Ensure the output of work is synchronized with the work of others.	1	2	3	4	5	6	7
CC02	Ensure an appropriate allocation of resources (e.g., information, time, reports).	1	2	3	4	5	6	7
CC03	Ensure the compatibility between expertise and work process.	1	2	3	4	5	6	7
CC04	Assign employees to tasks that appropriate with their task-relevant knowledge and skills.	1	2	3	4	5	6	7
CC05	Coordinate all the firm's functions.	1	2	3	4	5	6	7
CC06	Improved overall firm's coordinating capabilities.	1	2	3	4	5	6	7

<u>Section D: Demographic Profile</u>

Please indicate (/) in the appropriate information about yourself. Each question should only have **ONE** answer. All responses are strictly confidential.

1. **Firm Size (Number of Employees):**

	Less than 51
	51 -150
	151 -250
	251 – 500
	More than 500

2. **Firm's Established year:**

	Less than 1 year
	1-5 years
	6 – 10 years
	11 – 15 years
	16 years above

3. Firm's Ownership:

	Local
	Foreign
	Others

4. Current Department/Division

	Operational
	Quality
	Research and Development
	Environment Health and Safety
	Information Technology
	Human Resource
	Others

5. Current Managerial Position:

	Top Manager
	Sub Manager
	Middle Manager
	Executives
	Junior Executives Others (Please Specify:………………….)

6. Work experience years at the current firm.

	Less than 1 year
	1-5 years
	6 – 10 years
	11 – 15 years
	16 years above

7. Type of Digital Technologies adopted. [May tick more than ONE (1)]

1	**Internet of Things**
2	Big data and analytics
3	Cyber-Physical System
4	Cloud Computing
5	Additive Manufacturing
6	Simulation and autonomous robot
7	Artificial Intelligence
8	System Integration
9	Augmented Reality
10	Advanced Materials

8. Type of environmental initiatives/practices. [May tick more than ONE (1)]

1	**Lean production**
2	Life Cycle Assessment
3	Environmental Management System (EMS)
4	Emission reduction

5	Water Management
6	Material Efficiency
7	Product Recovery (recycling, reuse & remanufacturing)
8	Others

9. Rank the most (1) to least (6) challenges in digital technologies adoption.

	Lack of Finance
	Lack of Information
	Lack qualified employee
	Cyber security
	Standardization problem
	Research and Education costs

- **Thank you for your cooperation –**

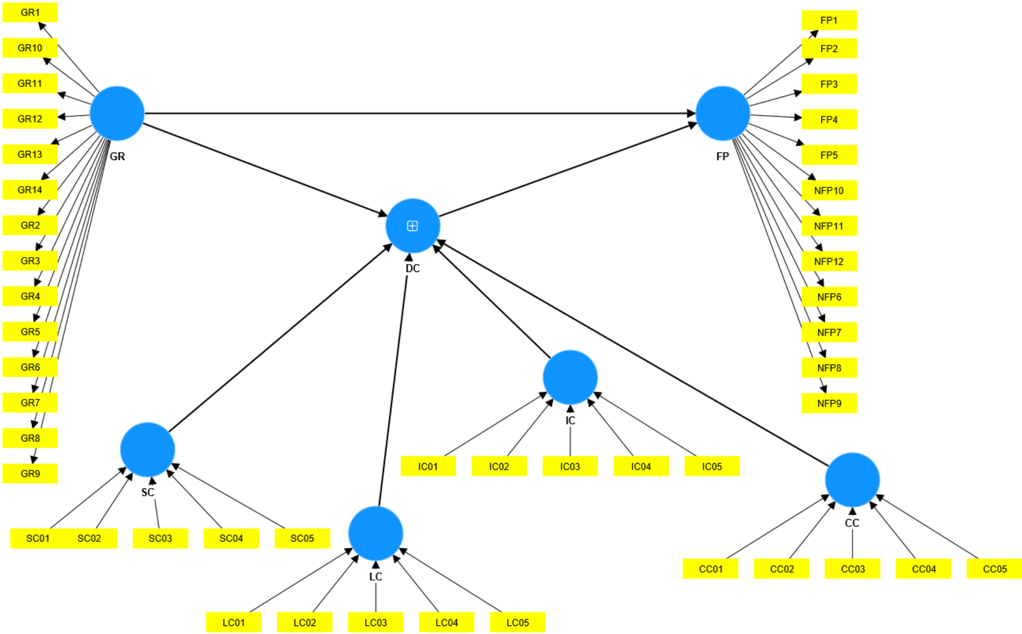
APPENDIX II: SKEWNESS AND KURTOSIS CALCULATION

Output of skewness and kurtosis calculation

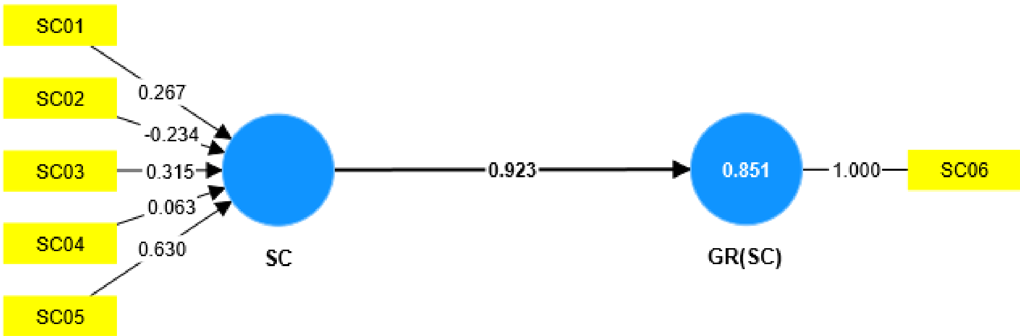
```
Sample size:  178
Number of variables:  6

Univariate skewness and kurtosis
   Skewness SE_skew Z_skew Kurtosis SE_kurt Z_kurt
FP    0.326   0.182  1.791   -0.676   0.362 -1.865
GR    0.152   0.182  0.833   -0.819   0.362 -2.260
SC    0.405   0.182  2.224   -0.666   0.362 -1.839
LC    0.451   0.182  2.475   -0.524   0.362 -1.446
IC    0.571   0.182  3.137   -0.530   0.362 -1.464
CC    0.573   0.182  3.146   -0.457   0.362 -1.262

Mardia's multivariate skewness and kurtosis
                 b          z      p-value
Skewness  4.974521 147.577444 3.512012e-10
Kurtosis 57.913805   6.749704 1.481459e-11
```

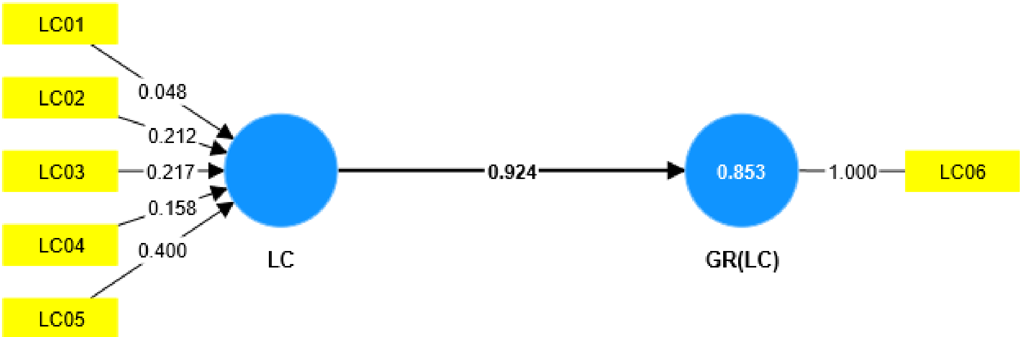
APPENDIX III: MEASUREMENT MODEL

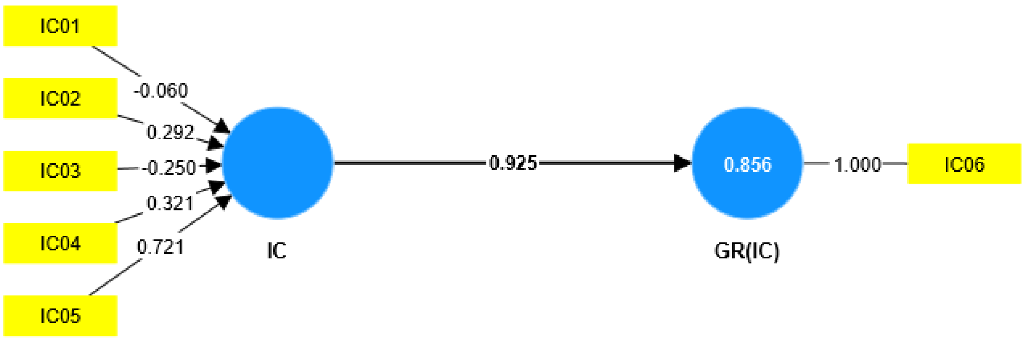
Measurement Model

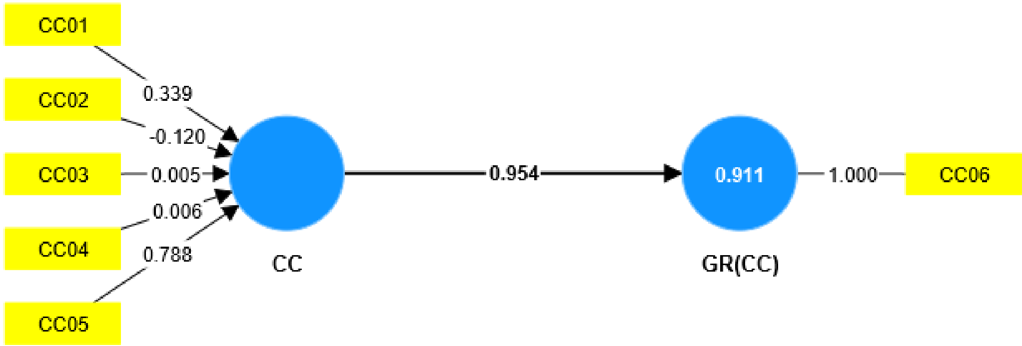


Convergent Validity









LVS Score Structural Model