CRITICAL FACTORS FOR GENERATIVE AI-DRIVEN GREEN VALUE CREATION IN SUPPLY CHAINS: A HIERARCHICAL FUZZY BEST-WORST METHOD APPROACH

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CANDIDATE'S DECLARATION

I, **ABHISHEK KUMAR SISODIYA**, hereby certify that the work which is being presented in the thesis entitled **"CRITICAL FACTORS FOR GENERATIVE AI- DRIVEN GREEN VALUE CREATION IN CIRCULAR SUPPLY CHAINS: A HIERARCHICAL FUZZY BEST-WORST METHOD APPROACH"** in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Mechanical Engineering, Delhi Technological University is an authentic record of my own work carried out during the period of January 2026 to May 2026 under the supervision of Dr. Pravin Kumar, Professor, Department of Mechanical Engineering, Delhi Technological University, Delhi.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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Critical Factors for Generative AI-Driven Green Value Creation in Circular Supply Chains: A Hierarchical Fuzzy Best-Worst Method Approach

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ABSTRACT

Green value creation has become a central objective for modern supply chains as organizations increasingly adopt circular and sustainable practices. While prior research has identified multiple environmental and sustainability-related factors across supply chain activities, the role of advanced digital technologies—particularly Generative Artificial Intelligence (GenAI)—in shaping and prioritizing these factors remains insufficiently explored. Moreover, existing studies often rely on conventional analytical approaches and lack structured decision-making frameworks capable of addressing uncertainty and expert subjectivity.

This study aims to identify and prioritize the critical factors influencing GenAI-driven green value creation in supply chains using a Hierarchical Fuzzy Best–Worst Method (HFBWM) approach. Based on an extensive review of the literature and expert consultation, five key supply chain dimensions—Supplier, Product, Packaging, Logistics, and Consumption—along with eighteen associated sub-factors are identified and validated. The HFBWM is employed to systematically capture expert judgments under uncertainty and to derive local and global priority weights.

The results reveal that product-related factors, particularly design for reuse, modular design, and circular product design, are the most influential drivers of green value creation, followed by sustainable packaging and consumption-oriented factors. Scenario-based analysis further demonstrates that GenAI capabilities—through interactive and non-interactive knowledge search—enhance decision-making quality, reduce dependence asymmetry, and strengthen inter-organizational collaboration, thereby reshaping the prioritization of green value creation factors.

The study contributes to the literature by integrating fuzzy multi-criteria decision-making with GenAI-enabled supply chain capabilities and offers a practical decision-support framework for managers seeking to prioritize high-impact sustainability initiatives. The proposed approach provides actionable insights for leveraging GenAI to support strategic green value creation in complex and uncertain supply chain environments.

Keywords: *Green value creation, Supply Chain, GenAI, HFBWM, Circular economy, Sustainable decision-making*

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
BWM	Best-Worst Method
CE	Circular Economy
CI	Consistency Index
CR	Consistency Ratio
CSC	Circular Supply Chain
CSCs	Circular Supply Chains
DA	Dependence Asymmetry
DOC	Digital Organizational Culture
EI	Equally Important
ERP	Enterprise Resource Planning
ESG	Environmental, Social, and Governance
FI	Fairly Important
GenAI	Generative Artificial Intelligence
HFBWM	Hierarchical Fuzzy Best-Worst Method
IKS	Interactive Knowledge Search
IoT	Internet of Things
JD	Joint Dependence
KS	Knowledge Search
LP	Linear Programming

MCDM	Multi-Criteria Decision-Making
NKS	Non-Interactive Knowledge Search
SCM	Supply Chain Management
SSCM	Sustainable Supply Chain Management
TFN	Triangular Fuzzy Number
TMS	Transactive Memory Systems
VI	Very Important
WI	Weakly Important

LIST OF SYMBOLS

Symbol	Meaning
ã	Fuzzy preference value
ã_B	Best-to-Others fuzzy comparison vector
ã_W	Others-to-Worst fuzzy comparison vector
ã_Bj	Fuzzy preference of Best criterion over criterion j
ã_jW	Fuzzy preference of criterion j over Worst criterion
ã_BS^j	Best sub-criterion preference within criterion j
ã_SW^j	Sub-criterion preference over Worst sub-criterion
ξ	Maximum deviation / optimization variable
ξ*	Optimal objective value
w_j	Weight of criterion j
w_S^j	Weight of sub-criterion S under criterion j
Gw_S^j	Global weight of sub-criterion
R(w_j)	Defuzzified weight value
l	Lower bound of triangular fuzzy number
m	Middle (most likely) value of triangular fuzzy number
u	Upper bound of triangular fuzzy number
Σ	Summation operator
∀	For all

CHAPTER 1

INTRODUCTION

1.1 Introduction

1.1.1 Overview of Sustainability and Environmental Concerns in Supply Chain Systems

The modern business world is undergoing considerable change with the emergence of growing environmental awareness, the issue of climate change, the loss of resources, and rising demands of the society to engage in responsible production and consumption habits. Though the industrialization and globalization have brought a faster growth in the economy, it has also increased environmental issues and this forces organizations to re-evaluate the conventional models of operation. As the backbone of industrial production and distribution, supply chain systems have been at the center of sustainability debate due to the fact that traditional management approaches of supply chain focused mainly on cost analysis, operational efficiency, inventory optimization, effectiveness of transportation as well as responsiveness to the market. Old-fashioned linear economics, that considered resource extraction, production, consumption, and disposal, frequently do not take into account the environmental impact of carbon emissions, loss in biodiversity, waste production, and overuse of resources (Christopher, 2016).

The high rate of industrial growth has also contributed to added environmental pressures as industries continue to consume high amounts of raw materials, energy, and water resources. Infrastructure involved in transportation networks that sustain global supply chains, as well as warehousing and disposal contribute to greenhouse gas emissions and augment the effects of pollution and landfill. Therefore, environmental sustainability has developed to become a marginal issue to a strategic business pertinence that determines organizational survival in the long-term (Seuring & Müller, 2008). An increased temperature, ecosystem disturbance, and catastrophic weather patterns in the form of climate change have strengthened the need to create a sustainable system of industrial change. Supply chains also contribute significantly to environmental degradation due to the existence of carbon intensive operations, inefficient use of energy, excessive packaging and production of wastes (Sarkis et al., 2011).

Sustainable supply chain management aims to ensure that environmental effects are minimal whilst remaining competitive in terms of the economy by encompassing sustainability principles in sourcing, manufacturing, logistics, distribution and after use processes. The strategy fits within the framework of Triple Bottom Line that focuses on environmental protection, economic growth, and social responsibility (Elkington, 1997). Increasing demands by stakeholders, shifts by consumers toward eco-friendly products, ESG-driven investment choices and thus more restrictive governmental policies have increased organizational stress to re-architecture supply chains to sustainability-centrical models (Carter & Rogers, 2008; McKinnon, 2018).

1.1.2 Emergence of circular economy principles in industrial operations

Alternation of industrial operating models has been keenly experienced because of the growing pressure on industries to minimize environmental degradation, increase resource utilization, and higher sustainability in the long run. Conventional industrial processes have tended to use a linear form of economy with the take-make-Dispose concept in which the raw materials are mined, converted into products, used and simply disposed of as trash. Despite the significant contributions, this model has made in terms of industrial growth and economic development in the nineteenth century, its environmental and economic long term effects have become more pronounced. Issues like depletion of resources, overproduction of waste, pollution, loss of biodiversity and climate change have made industries to rethink the traditional production and consumption of goods and services. In reply, the circular economy has come across as one of the viable sustainable frameworks to match the level of industrial productivity of the environment with responsibility through enhancing material and brand recycling, lowering waste levels, and optimizing resource usage (Geissdoerfer et al., 2017).

A key building block of the philosophy of the circular economy is the performance economy model suggested by Stahel (2016) that focuses on the expansion of the life cycle of products by means of repair, maintenance, reuse, remanufacturing, and upgrading. This is an improvement that aims at maximizing the value and utility of existing goods instead of supporting keeping on producing more goods, hence enhancing durability, longevity and saving of resources. The rising environmental awareness and reliance on exhaustible natural resources have only contributed to the acceptance of the principles of the circular economy in industries. This fast industrialization, urbanization and population boom has increased the demands of metals, minerals, fossil fuels, water, and agricultural inputs which are normally accompanied by ecological destruction, habitat destruction, pollution, and carbon emissions. The concepts of the circular economy can be used to solve these issues by decreasing the use of virgin resources extraction and promoting material recirculation, recycling, and resource sustainability. As a result, the circular economy is considered to be a promising direction on the way to the industrial sustainability, showing the balance between economic growth and environmental protection (Ellen MacArthur Foundation, 2015; Stahel, 2016).

1.1.3 Growing significance of green value creation in sustainable business ecosystems

The growing interest in environmental sustainability has changed the generation of value in contemporary business ecosystems. Conventional business models mainly were tied to financial metrics like profitability, market growth, operational effectiveness and wealth maximization to its shareholders. But nowadays business landscapes are more and more requiring a larger scope of value creation strategies which combine environmental stewardship, social responsibility and sustainable resource management. This has given rise to green value creation as a strategic model which integrates both economic performance and benefits in the environment and society. Green value creation tries to focus on the sustainable business activity that has few or no impact on ecological destruction and improves organizational performance and stakeholder value via ecologically responsible innovation, efficient resource use, pollution prevention, waste reduction, adoption of renewable energy, circular production systems, and eco-friendly operational systems (Hart and Milstein, 2003). Organizations are becoming more convinced of the fact that sustainability efforts help in protecting the environment and also in operational efficiency, customer interaction, development of innovation, and long-term competitive edge. The increasing environmental issues such as climate change, biodiversity extinction, pollution, short supply of resources, ecological degradation and greenhouse gases, have raised pressure on corporations to act responsibly on their environment. Businesses are under increasing pressure by governments, consumers, investors, the regulator and civil society to incorporate sustainability as part of their main operations (Porter and Kramer, 2011). Previously the understanding of environmental responsibility was that it is a compliance measure that is accompanied with regulation and extra costs of operation. Nevertheless, recent studies on sustainability have shown that environmental program can enhance organizational value by making it more cost effective, innovating, better differentiating companies in markets as well as minimizing operational risks (Hart, 1995). Creation of green value is also consistent with the stakeholder theory, which focuses on the long term organizational success by the consideration of the interests of the customers, employees, suppliers, investors, regulators and communities (Freeman, 1984). Since the environmental footprint of industrial operations is quite high, companies are increasingly developing environmentally friendly policies to minimize ecological footprint and improve its long-term competitiveness and legitimacy.

1.2 Evolution of Supply Chain Management

During the last few decades, Supply Chain Management (SCM) has transitioned quite a bit since its initial focused use as an operational tool, capable of designing projects that allowed procurement, transportation, and logistics coordination to a more strategic discipline where sustainability, new technological development, and circular economy are reflected. The change is related to the wider industrial transformation due to globalization, technological progress, competitive business landscapes, environmental issues, and rising stakeholder demands. Contemporary supply chain has ceased being just the product delivery system but has become an integrated ecosystem that has the ability to affect the economic performance, environmental sustainability, social responsibility, as well as the organizational resilience. The previous production methods in industries had focused primarily on efficiency in production and stock availability making the suppliers, manufacturing, distributors, and retailers to coordinate with one another in a fragmented manner. Minimal technological infrastructures and lack of information sharing also led to inefficiency along industrial value chains (Christopher, 2016).

SCM formal development accelerated in the late twentieth century as organizations faced rising consumer demands, product complexity and globalization forced them to increase coordination among participants in the supply chain. Competitive advantage was now highly linked not just with internal operational efficiency, but also with successful synchronization among suppliers, manufacturers, logistics firms and networks (Mentzer et al., 2001). Globalization has increased availability of inexpensive labor, a wider supplier network, and an increased number of customer segments, providing flexibility and cost reduction, but creating issues regarding risk management, complexity of coordination and sustainability. The SCM was further changed with technological advances in Enterprise Resource Planning (ERP) systems, electronic data interchange, inventory optimization tools, and advanced analytics, enhancing information sharing, business visibility, decision accuracy, and decision making (Chopra and Meindl, 2019).

Modernization of supply chains has increased through the appearance of digital technologies, including artificial intelligence, cloud computing, big data analytics, blockchain, automation, and the Internet of Things, which allow predictive and responsive operational strategies. At the same time, growing fears over climate change, the loss of resources, and environmental degradation have broadened SCM goals beyond the economics of optimization to one that is mindful of the sustainability and social well-being (Seuring and Muller, 2008). Modern supply chains are becoming much more defined by the idea of a circular economy based on the principles of recycling, recovery of resources, minimization of waste, reverse logistics, and closed-loop processes, which defines SCM as a major strategic contributor to competitiveness, resiliency, and sustainability of the supply chain in the long term.

1.2.1 Traditional Supply Chain Systems

Traditional supply chain systems developed in eras of industrial growth where there was mass production, centralized manufacturing, and management philosophies which focused on efficiency. The conventional supply chain was mainly concerned with optimizing the procurement, production, inventory management, warehousing, and transportation processes in order to maximize operational efficiency, reduce costs and also offer product availability. To a large extent these systems adhered to a linear type of economic system where resources followed a linear flow of extraction of a raw material and production, distribution, consumption, and subsequent disposal. The flow of materials adhered to a one-way model and there was minimal focus on the aspect of resource recovery or sustainability. The exchange of information among the supply chain participants was rather weak, which led to the problem of coordination among suppliers, manufacturers, distributors, and retailers (Christopher, 2016).

The principle of mass production had an enormous impact on the conventional supply chain design, when it encouraged the need to standardize the manufacturing process and concentrate the manufacturing plants to attain economies of scale. Planning in production focused on production maximization and stocking up to handle demand variability and buffer stock was held to handle forecasting uncertainty and operation disturbances. The conventional supply chain organizational structures tended to be hierarchical so that the stakeholders worked in isolation and had a localized performance goal as opposed to an integrated ecosystem optimization performance. Confined dissemination of information and the poor coordination in decision making processes established functional silos that were performance impediments. Minimization of costs was identified as the prevailing form of performance and determinant on procurement decisions, selection of suppliers, logistics planning, inventory management strategy. The suppliers were chosen mostly by considering the price factor, and the choices of transportation and warehousing were aimed at lowering the costs of operations (Christopher, 2016).

The supply chains of the past too were dependent on historical forecasting of demand and manual systems of planning, which usually led to inaccurate forecasts, stocking errors, and inefficiencies since they lacked sufficient analytical options. Globalization also redefined the nature of supply chains through increased supplier numbers and promoting outsourcing of manufacturing to geographically spread manufacturing hubs to gain economies of scale. As much as globalization enhanced efficiency in undertaking economic activities, it also increased the level of problems with operations and supply chain risks. In addition, the traditional supply chains were characterized by an extreme degree of environmental restrictions due to its linear pattern of resource utilization. The process of extracting resources, manufacturing, transporting goods, and creating wastes were contributing to an ecological degradation, and environmental externalities, whereas limited focus to resource recovery and waste minimization limited long-term sustainability performance (Christopher, 2016).

1.2.2 Sustainable Supply Chain Management

Sustainable Supply chain Management (SSCM) has proved to be a strategic intervention in focus of addressing the increasing environmental issues, stakeholder expectations and in the sustainability of industries in contemporary business landscape. The conventional supply chain systems mainly focused on cost minimization and efficiency in operations but failed to consider environmental responsibility and sustainability in the long term. SSCM incorporates environmental, social and economic aspects throughout the procurement, manufacturing, logistics, distribution and post consumption efforts to establish organizational competitiveness and reduce environmental effects and increase the stakeholder value (Carter and Rogers, 2008). The idea is very similar to the Triple Bottom Line framework, that considers economic prosperity, environmental preservation, and social welfare as the crucial measures of sustainable development (Elkington, 1997). The concept of environmental sustainability in the framework of SSCM is concerned with prevention of pollution, minimization of carbon emissions and efficient use of resources, minimization of waste, sustainable sourcing and optimization of resources. The ecological performance is growing to be environmentally responsible operating systems which organisations are introducing to cut on the environmental burdens. Social sustainability has also emerged as a vital SSCM aspect, where ethical labor, workplace safety, initiatives of supplier diversity, ensuring human rights, active relationship with the community, and employee welfare portfolios all came into scope. Economic sustainability aspects focus on ensuring that their profitability is sustainable over the long term, organizational strength, efficiency of operations, minimization of risks, and generation of trust among stakeholders. The economic advantages of sustainable supply chains include greater efficiency, ability to innovate, and increased risk management processes. Green procurement practices also help in enhancing the application of SSCM by adopting the supplier sustainability principles like environmental norms, responsible sourcing norms, energy-saving measures, and ethical operational practices. Green logistics programs also add a lot to the sustainability objectives by optimizing transportation, reducing fuel consumption, lowering greenhouse gas emissions and increasing efficiency. The evolving use of alternative fuel mechanisms and low emission transportation technologies facilitate the environmentally sustainable logistics practices. Also, through the digital transformation technologies, SSCM capabilities have been enhanced by enhancing monitoring sustainability performance and operational efficiency. Artificial intelligence assists in the process of demand forecasting and optimization of resources, analytics with big data is the process that should be used to increase the sustainability performance measurement, and Internet of Things (IoT) infrastructure is the technology that will help to improve the supply chain monitoring and increase monitoring of the environment. Therefore, SSCM is an imperative model of business sustainability and competitive advantage in the long run. (Carter & Rogers, 2008; Elkington, 1997)

1.2.3 Circular Supply Chain Concept and Development

Circular Supply Chain (CSC) systems are a progressive model in the realm of sustainable supply chain management, focused on resource circulation, waste minimization, and regenerative value creation. Circular supply chains intend to keep materials, components and products within economic cycles longer (through reuse, remanufacturing, recycling, refurbishing, repair and reverse logistics efforts unlike traditional linear supply chains founded on extractions, productions, consumption and disposal (Genovese et al., 2017). The idea was developed due to growing concerns surrounding the environment like the depletion of resources, over-production of waste products and climate changes related to traditional systems of production. One major resource recovery principle of CSC is to collect, treat, and reuse post-consumption materials in the industrial production system, minimizing the use of virgin resources and enhancing the efficiency of materials. Reverse logistics is very crucial as it facilitates the returns of products, recovery of components, repairing and recycling of the products, and thus aids in the recirculation of materials. Another useful feature is product design optimization, which stresses on durability, repairability, modularity, and recyclability, as the way to enhance resource efficiency and longevity of the product. Circular supply chains can also be boosted by technologies like artificial intelligence, blockchain, and Internet of Things (IoT) that allow predictive maintenance, tracking of materials, and lifecycle medical. Furthermore, to achieve the successful circular ecosystems, suppliers, manufacturers, logistics providers, consumers, recycling institutions, and policymakers have to cooperate to ensure the closed-loop processes. Circular supply chains can help promote environmental sustainability as they reduce waste, limit carbon emissions, conserve natural resources, and safeguard ecosystems, as well as provide economic advantages to operations in terms of increased operational efficiency, resource productivity, etc. (Genovese et al., 2017).

1.2.4 Transition from Linear Economy to Circular Economy Models

The evolution of the linear economy models into the systems of a circular economy constitute the initial move towards the sustainable industrial development. The traditional linear economic systems used to operate on a take-make-Dispose model, in where resource deriving, production, consumption, and disposal were emphasized. Despite the fact that this model was instrumental in the development of industries and achieving economic growth, its effects in the long-term, such as the depletion of resources, the accumulation of pollutants and climate change, biodiversity loss, and rising heaps of landfills revealed several significant constraints to its sustainability (Geissdoerfer et al., 2017). To this, circular economy models came out as regenerative systems aimed at maximising resource efficiency, keeping material value and reducing degradation to the environment. Circular models encourage recycling, reusing, the introduction of renewable energy, practicing sustainable sourcing, and designing products in a circular manner to minimize reliance on finite resources. The shift demands massive change in operations in the form of procurement, manufacturing, logistics and consumption systems. This transformation is accelerated even more by the technological aspect as Artificial Intelligence (AI) increases resource optimization, the big data analytics increase sustainability monitoring, and Internet of Things (IoT) technologies increase operational visibility and assist in constantly increasing the level of circular performance.

Besides, governments and policymakers across the world are pushing towards the adoption of the circular economy by adopting environmental policies that facilitate the adoption of recycling programs, waste management, and renewable energy use, and sustainable production models. These technological, organizational, and policy interventions are all enabling a paradigm shift of resource-intensive linear industrialization to resilient and environmentally friendly circular economic systems capable of supporting long-term economic growth, as well as ecological preservation (Geissdoerfer et al., 2017).

1.3 Concept of Circular Supply Chains

Circular Supply Chains (CSCs) are a recent creative mode of operation in consideration of industrial expectations on sustainability, resource savings and minimization of environmental harm. The traditional supply chains have minimal economic cycles that are linear based on extraction, production, distribution, consumption, and disposal. Whereas these systems have played a big role in industrial progress, issues about resource drying up, pollution, climatic changes and generation of wastes, have brought forth their short-term constraints (Genovese et al., 2017). Circular Supply Chains help solve these issues focusing on the circulation of resources, the reduction of waste, the prolongation of life cycle of products, and sustainable creation of value. In contrast to the linear systems where the flows of materials are unidirectional, CSCs build up the resource regeneration processes that facilitate the idea of reuse, repair, remanufacturing, recycling, as well as recovery of resources in the industrial ecosystems (Kirchherr et al., 2017). The principles of the circular economy underlie CSCs, which combine sustainability efforts in procurement, manufacturing, logistics, distribution and post consumption recovery. Their evolvement highlights shifting industrial priorities, with organizations becoming more about the environment and economic competitiveness. An increase in stakeholder awareness, tighter environmental rules, and an increased focus on Environmental, Social, and Governance (ESG) indicators of performance have further increased the pace of the adoption of the practice of the circular supply chain. Companies are also reconfiguring supply chains at a record pace in order to become responsible and efficient simultaneously in terms of ecology and workability. The CSC implementation has also been enhanced by technological advances, which enhanced resource optimization and sustainability performance measurement. Artificial intelligence and technologies like predictive maintenance and operational optimization improve operational efficiency, Internet of Things (IoT) enhances the monitoring of product lifecycle, blockchain enhances material traceability and big data analytics enables efficient sustainability evaluation. Combined with other digital innovations, they help to manage resources more efficiently and are part of the shift to regenerative and sustainable industrial regimes (Genovese et al., 2017; Kirchherr et al., 2017).

1.3.1 Definition and Characteristics

Circular Supply Chains (CSCs) refer to closed-loop supply chain systems that aim to foster nature regeneration by recirculating materials, minimizing waste, recovering resources and maintaining sustainable values in product life cycles (Farooque et al., 2019). By contrast to the classical linear supply chains when the main focus was put on production efficiency and distribution of the products, the CSCs target to keep goods, materials and components in economic systems over the long duration of time with the help of the circular distribution of resources. Resource circularity, which encompasses reuse, recycling, refurbishment, repair, remanufacturing, and recovery, is a hallmark of CSCs and is considered a way of conserving material value over many working lifespan. Rather than considering products as waste once consumed, a circular system focuses on preserving product resource value and minimising environmental impacts. Closed material flow, where post-consumption materials are returned to industrial loops and less virgin resource wastage needs to be seen as the other key characteristic, which leads to lower sustainability performance. The operation of resource efficiency does not go off-center either because a circular system aims to maximize material use and reduce waste at procurement, production, logistics, consumption stages. CSCs also contrast with traditional systems in offering orientations of lifecycle, taking into consideration sustainability consequences of fostering product design and sourcing, manufacturing, usage, recovery, and disposal. Maintenance, repair system, modular design and technological upgradability are other important features that prolong product longevity and minimize waste, thus enhancing utility of products. Also, CSCs rely greatly on corporate teamwork between suppliers, manufacturers, logistics service providers, consumers, technology developers, recycling organisations, and policymakers to create cohesive ecosystems to enhance sustainability performance and operation efficiency (Farooque et al., 2019).

1.3.2 Principles of Circular Supply Chains

The principles used by circular supply chains lead to green operations and an environmentally friendly industrial transformation. One of the fundamental principles is designing out waste and pollution, i.e., the generation of waste by design decreasing waste by means of creating a sustainable product design, efficient manufacturing, and minimum resource usage instead of viewing waste as a byproduct (Ellen MacArthur Foundation, 2015). Another principle, which is of primary importance, is resource preservation: the less reliance on virgin materials through material efficiency and increased recovery of resources, and consequently, sustainability and minimized risk of supply are secured. Circularity is further enhanced by the product life extension which extends the extent of products (maintenance, repair, renovation, and modular design) enabling them to maintain a longer usability period, and reducing the rate that new production processes are undertaken. The reuse and redistribution systems are also critical since they allow the retention of value that the product can be used again before having to go through recycling or recycling. On the same note, remanufacturing reinstates a comparable performance to the product to that of brand-new products, decreases raw materials utilization and boosts resource utilization. The principles of recycling assist the industries to reduce environmental effects and incorporate back into production mechanisms so as to assist in recovery and reuse of materials to optimize resource utilization. Another crucial consideration is regeneration, which is recommended to enhance the application of renewable energy, sustainable sourcing, and the restoration of the ecosystem to enhance a stronger environmental resilience in the long run. Circular supply chains are also based on systems thinking, as suppliers, manufacturers, logistic providers, consumers, and recycling entities are all part of interdependent industrial ecosystems where joint decisions enhance sustainability results. The digital enablement has also become a more critical aspect in the circular supply chains, as technologies, like artificial intelligence, can enhance efficiency in the process of resource distribution, the Internet of Things can increase the visibility of operations, and blockchain can bolster the mechanisms of material traceability and sustainability optimization (Ellen MacArthur Foundation, 2015).

1.3.3 Components of Circular Supply Chain Systems

Circular supply chain systems are structural systems which have been integrated and are multidimensional in nature and which have been developed in a bid to foster resource regeneration, material recirculation and optimization of sustainability throughout the supply chain lifecycle. Sustainable procurement can be considered as one of the central elements as it focuses on the sourcing practices that are environmentally friendly, including recycled materials, renewable resources, ethical suppliers, and production processes that conserve resources. The manufacturing process is another important aspect, with the terms of circular manufacturing being reduced waste production, energy efficiency, and incorporating sustainable production and manufacturing technologies to achieve better environmental results in the long term (Farooque et al., 2019). Inventory and resource management systems also add to moving towards a circular economy as they help optimize the use of materials and and minimize inefficiencies with smart operational practices. Another critical factor is logistics infrastructure that enables forward product delivery and reverse material flows that are needed during recovery operations. The systems of the reverse logistics provide the process of products collection, recycles, repair, restauration and re-manufacturing when the possibility of the valuable materials recovery is used as well as the extension of the products circles of life (Genovese et al., 2017). Material recovery facilities also enhance circular systems by reprocessing post-consumption materials to be reintroduced into the industrial production process. Circular supply chain performance is growing with technological infrastructure using artificial intelligence, predictive maintenance systems, big data analytics, and blockchain technologies that further identify predictive capabilities, environmental monitoring, and supply chain transparency (Govindan and Hasanagic, 2018). The cooperation of stakeholders and consumer involvement also remain to be crucial dimensions because sustainable consumption patterns, recycling behavior, and product returns mechanisms also play a crucial role in defining the performance results of the circular form. The coordination of procurement, manufacturing, logistics, recovery systems, technology and stakeholders interaction, respectively, enhances the resource productivity and promotes environmental sustainability goals in the context of circular supply chain systems (Farooque et al., 2019; Genovese et al., 2017).

1.3.4 Closed-Loop Supply Chain Mechanisms

The mechanisms of the closed-loop supply chain are some of the key components of operations that are central to the circular resource management systems. Closed-loop systems create the material circulation mechanisms that allow products and components that first goes through consumption stages to be channeled back to useful productive industrial use (Guide & Van Wassenhove, 2009). Conventional supply chain systems focus mainly on forward operational processes that entail the supplier buying activities, manufacturing processes, logistics systems as well as the distribution processes. Closed-loop supply chains also enable the incorporation of reverse operating capability that helps in introducing materials recovery mechanisms. The system of product returns is one of the initial closed-loop operation systems. Product collection facilities assist in reclaiming used products after the consumption stints among the consumers. Products can be repaired, which reinforces the outcome of product longevity. The repair interventions do not only retain the product utility abilities but also lower the disposal needs. In addition to material productivity capabilities, refurbishment systems help. Refurbishment comes with the ability to restore the functionality of the products furthering lifecycle periods. Similar processes bolstering closed-loop operational efficacy are remanufacturing mechanisms. Restoration interventions are often done on product components allowing its reintroduction to industrial production systems. Another valuable closed-loop capability that facilitates the mechanisms of circulation of resources is recycling infrastructure. Online technologies enhance operative performance of the closed loops. The systems of the Internet of Things enhance the lifecycle monitoring. Possible technologies on artificial intelligence enhance predictive optimization of recovery.

1.3.5 Reverse Logistics and Resource Recovery Systems

Reverse logistics, resource recovery systems can be regarded as core operational capabilities in the possible functioning of the circular supply chain. Reverse logistics are those mechanisms that help in product transportation between the consumption and recovery destinations which may include, but is not limited to, recycling, repairing, refurbishing, remanufacturing or discarding of products (Rogers and Tibben-Lembke, 1999). The main focus of the traditional logistics systems is the forward distribution capabilities. The reverse logistics is able to expand the functionality of operations by incorporating backward resources circulatory systems that enhance performance of the sustainability. Essential reverse logistics infrastructure is product collection systems. The products are recovered using collection mechanisms after the phases of usage. Sorting helps to enhance the effectiveness of the recovery, including the categories of materials that should be sorted based on the possibilities to recycle the material, refurbish it, repair it, or dispose of it. The transportation infrastructure facilitates material recovery process by establishing good reverse flow coordination systems. There are recycling systems which help in processing recovered materials and making them available to be reused in industrial production processes. The remanufacturing infrastructure enhances the ability to preserve value, since the used products may be restored to operational levels of functioning. Repair processes help in the extension of the product life increasing pressures against waste generation. Resource recovery mechanisms enhance the soil performance in environmental sustainability by limiting the reliance on the use of virgin material extraction processes. The capabilities of reverse logistics optimization get more robust due to the use of artificial intelligence technologies. The predictive analytics systems enhance effectiveness in collection. Material recovery is a decision-making approach that is increased with the help of big data analytics.

1.4 Green Value Creation in Circular Supply Chains

The philosophy of green value creation is now taking root as a strategic method of importance in contemporary industrial eco-systems because the promotion of sustainability is driving supply chain activities. The traditional supply chains were mainly concerned with the profitability, operational efficiency, increase in productivity, and market growth. Nevertheless, emerging environmental issues, shortage of resources, demands of stakeholders and critical demands by the authorities have stimulated organizations to reform traditional value creation models to become sustainability-determined ones. Green value creation can be defined as the process whereby the creation of environmental, economic and social value is done systematically by the use of sustainable operational activities that utilize resources in the most optimal way, reduce the amount of waste that is created, limit the effects on the environment, and increase the welfare of the stakeholders (Hart and Milstein, 2003). The Circular Supply Chains (CSCs) would form an appropriate framework of developing green values due to their focus on the regeneration of resources, recovery of resources, sustainable production processes, recycling systems, and product life cycle. In contrast to the conventional linear supply chains, circular supply chains emphasize the conservation of resources, the removal of waste products and the integration of renewable material, benefiting the sustainable environment and efficiency of the supply chains. Organizations are finding it to be important that sustainability programs do not just meet the compliance needs but also generate the strategic advantages of new areas of innovation, optimization of operations, competitive advantage, and expanding markets (Porter and Kramer, 2011). Circular supply chains enhance green value generation further by sustainable procurement, effective production systems, reverse logistics, recycling interventions, and remanufacturing capabilities that ultimately enhance environmental protection and economic resilience. The technological solutions have speeded up this change, improving demand forecasting, inventory optimization, sustainability performance monitoring, resource visibility, and supply chain visibility based on artificial intelligence, big data analytics, Internet of Things (IoT), and blockchain technologies. Such technologies facilitate making environmentally friendly decisions and promote credibility among stakeholders. Consumers are becoming interested in sustainable products, investors are focusing on indicators of Environmental, Social, and Governance (ESG), performance, and regulators are insisting on the environmentally responsible nature of industrial activities. Thus, organizations that incorporate the concept of green value creation in the process of a circular supply chain find themselves better equipped to climate risk, regulatory uncertainty, and resource scarceness which enhance long-term sustainability, competitiveness and industrial resilience (Hart and Milstein, 2003; Porter and Kramer, 2011).

1.5 Generative Artificial Intelligence: Concept and Foundations

Generative Artificial Intelligence (Generative AI) has become one of the promising technological trends changeing the digital ecologies, industrial processes, and the way organizations work and make a decision. The aggressive development of computational intelligence and machine learning systems, neural networks, and mass data processing has spurred the shift of Artificial Intelligence (AI) out of rule-based automation systems to more advanced generative models that are capable of generating new content, pattern recognition, supporting intelligent decisions, and providing predictive results. The innovations have played a significant role in development in sectors like health care, education, banking, research and development, sustainable activities and supply chain management. The term Artificial Intelligence is widely used as a collection of algorithms and computational systems equipped to imitate various human intellectual capabilities such as learning, reasoning, problem-solving, adapting and generating knowledge (Russell and Norvig, 2021). Previous AI systems were primarily engaged in classification, predictive analytics, optimization and automated decisions, whereas Generative AI goes beyond a capability of analyzing data and actually creates text, images, audio, code, simulations, artificial data sets and predictive scenarios based on learned data representations. Generative AI is being more and more viewed as a strategic resource that can be used by organizations to improve productivity, innovation, intelligent automation, and sustainability performance and, more crucially, decisions in support of digital transformation goals. What is relevant in circular supply chains and green value creation structures, in particular, is that organizations need to use smart resources to optimize their resources, predict demand, minimize waste, and measure their sustainability performance. Generative AI enhances these operations by using predictive intelligence, adaptive operations, and sustainability optimization analytics. The roots of Generative AI date back to the progress in computation learning, neural network, probabilistic models, deep learning methods, and technologies of natural language processing. Advancement in cloud computing, graphics processing right and broad availability of large amounts of data have only increased the production and release of sophisticated generative models. Since organizations favor work in more uncertain and technologically changing environments, Generative AI facilitates the dynamism of decision-making and competitive advantages. Therefore, Generative AI is not just a technological breakthrough but a paradigm shift that defines the way industry systems of the future work, strong business models, and intelligent ecosystems can be sustainable (Russell and Norvig, 2021).

1.6 Generative AI Applications in Supply Chain Systems

With rising levels of digital transformation and an increased complexity in operations, Generative Artificial Intelligence (Generative AI) has become one of the new, revolutionary technologies in the realm of supply chain management. The contemporary supply chains are dynamic and are marked by changes in the customer demands, sourcing networks across the world, resource constraints, pressure to sustainability, and uncertainty. Older methods of supply chain management that placed a lot of reliance on the past data, manual calculations and making decisions, statistical use of probabilities and forecast is proving inefficient in handling these complexities. As a result, the industries are moving to smart technologies, which enhance responsiveness, flexibility, resilience, and sustainability performance. Generative AI is no longer limited to the traditional Artificial Intelligence models that only perform prediction and classification effectively because it also facilitates more complex applications such as intelligent forecasting, scene generation, generating synthetic data, adaptive learning, process optimization, and simulation modeling (Dwivedi et al., 2023). The capabilities empower the organizational decision-making process through predictive intelligence capabilities, operational flexibilities, and optimization in real time. The application of Generative AI takes step with Industry 4.0, such as automation, digitalization, cloud computing, sophisticated analytics, cyber-physical system, and Internet of Things (IoT) technologies that work together to facilitate intelligent supply chain ecosystems (Ivanov et al., 2019). Generative AI is also associated with the supply chain resilience by assisting the organizations to react to the disruptions caused by climate problems, geopolitical uncertainty, pandemics, transportation disruption, economic uncertainty and resource scarcity. Risk management and continuity is enhanced with predictive modeling, adaptive planning systems and scenario simulations. Moreover, the sustainability goals are hastening the use of Generative AI in supply chains. Organizations pay more attention to the minimization of waste, management of carbon emissions, optimization of renewable resources, the organization of the system of reverse logistics, and the systems of the work of circles. Impactful sustainability and resource optimization: Generative AI aids in making environmentally-optimized decisions, leading to better sustainability results and resource usage. The growing variety of applications in the demand forecasting, inventory optimization, predictive analytics, operational automation, and sustainability optimization frameworks prove its strategic role in the development of intelligent, resilient, and sustainable supply chain systems capable of tackling the contemporary challenges in the industrial environment (Dwivedi et al., 2023; Ivanov et al., 2019).

1.7 Generative AI-Driven Green Transformation

The idea of generative AI-based green transformation can be viewed as a significant change toward environmentally responsible industrial development, combining intelligent technologies with a sense of environmental responsibility, resource conservation, and the principles of a circular economy. The increased environmental pressures, such as global warming, greenhouse gases, biodiversity degradation, industrial effluents, waste generation, and over exploitation of natural resources have necessitated organizations to re-architecture systems of operation to enable them to realize the objectives of sustainability. Green transformation: Green transformation is the systematic organizational as well as industrial transition that aims to ensure a reduction in environmental effects, increased resource efficiency, enhanced operational stability and long-term sustainability. Traditional sustainability initiatives focused mainly on regulatory compliance, minor enhancements in processes, and environmental monitoring, but over time the complexity of industries and environmental uncertainty has augmented the need to look into adapting and smart technological solutions (Dwivedi et al., 2023).

Generative Artificial Intelligence (Generative AI) has become a transformative technology that is able to facilitate sustainability with the aid of intelligent decision making, predictive analytics, resource optimization and sustainability oriented operational planning. In comparison to the classical Artificial Intelligence solutions, which primarily involve analytical forecasting, Generative AI allows creating simulations of scenarios, learning and knowledge discovery on-the-fly, and modeling synthetic environments, which allows organizations to be proactive about environmental issues. Industrial 4.0 technologies such as cloud computing, Internet of Things (IoT), machine learning, big data analytics, blockchain, and automation have also enhanced Generative AI usage in sustainability transformation by establishing networked interdependent industrial systems that are more environmentally efficient (Kamble et al., 2018).

Generative AI-based green transformation is becoming an increasing factor that affects manufacturing, procurement, logistics, energy management, waste recovery, and circular supply chain systems that enhance sustainability visibility, environmental forecasting, waste reduction, and resource productivity. The intelligent sustainability technologies assist organizations in preparing robust and environmentally accountable models of operations that are able to respond to resource constraints, climate change, regulation shifts, and the dynamic demands and anticipations of the stakeholders. Moreover, AI-enhanced sustainability systems enhance the ability of organizations to remain competitive in the long run by enhancing organizational flexibility and resilience. Generative AI, in turn, has become a strategic technological asset that can facilitate environmentally conscious industrial change and provide more intelligent, adaptable, and efficient resource-powerful business ecosystems (Dwivedi et al., 2023; Kamble et al., 2018).

1.8 Critical Factors Influencing AI-Driven Green Value Creation

The implementation of Artificial Intelligence (AI) continues to change how sustainability is managed, how a circular economy is implemented, and green values are created within industrial ecosystems. Companies can now see the AI as a strategic technological force that leads to increased efficiency in operations, better use of resources, stronger environmental performance, and enables circular development of supply chains. Green value creation is a concept of creating environmental, economic, operational and social value by conducting operations in a sustainable manner focusing on effective use of resources, minimizing waste, reducing pollution, curbing carbon emission, and improving stakeholders welfare (Hart and Milstein, 2003). AI plays a key role in achieving these goals by providing predictive analytics services, intelligent allocation of resources, automated monitoring solutions, operational optimization services, and adaptive decision making. Additionally, recent Generative Artificial Intelligence developments have increased sustainability prospects allowing the simulation of scenarios, smart forecasts, environmental decision support, sustainability analytics optimization.

Nonetheless, the effective development of AI-based green values is based on several mutually dependent elements that affect technological utilization and sustainability programs. Some barriers that are often faced in organizations include infrastructure constraints, technology complexity, lack of capabilities, organizational resistance, governance and an uncertain regulatory environment. Such limitations suggest the need to establish the key determinants that can enhance sustainability transformation in an AI-enabled and enhance green performance outcomes in the long term.

Due to the growing complexity of sustainability transformation projects, multidimensional frameworks must be represented by integrating technological preparedness, organizational preparedness, environmental preparedness, operations capabilities and digital preparedness. The contemporary industrial complex demands not only the developed technological framework but also structural adaptability, cyber-resilience, sustainability management procedures as well as regulatory compliance facilities to facilitate successful implementation of AI. The most important influencing factors can thus be classified under the technological dimensions, organizational capabilities, environmental and regulatory conditions, operating competencies and digital infrastructure readiness.

These dimensions work in a mutually dependent way and interrelate to create organizational effectiveness in the introduction of sustainability transformation initiatives and smart environmental management systems. Furthermore, AI adoption success is increasingly dictated by ecosystem-wide alignment of stakeholders, technological platforms, and rules, and the capacity of digital transformation. Knowledge of these influencing dimensions helps organizations enhance the models of sustainability implementation, fast-tracking the creation of green values, and sustaining development of environmentally compatible industrial complexes that can raise the sustainability targets and the evolution of the circular economy (Hart and Milstein, 2003).

1.9 Sustainability and Circular Economy Perspectives

The concept of sustainability and the notion of a circular economy have become critical frameworks in line with the increasing environmental issues, such as climate change, biodiversity loss, resource depletion, pollution, and unsustainable consumption patterns. The previous industrial systems were mainly linear economic systems which are founded on resource extraction, production, consumption as well as disposal. Though these practices have ensured the growth and development of industries, with the growing environmental pressures, these practices have been pointed out to be limited and ecologically inclined in the long term. Sustainability thus became a paradigm in terms of balancing environmental protection, economic prosperity and social well-being to provide a development that meets the present needs without jeopardising the capacity of the future generation to meet their needs (Brundtland Commission, 1987). Sustainable development focuses on combing the elements of environmental responsibility with economic and social goals in order to assist in the development of society in the long term.

The escalation of sustainability issues has promoted the use of circular economy models, which focus on efficiency of resources, minimization of waste, regenerative industrial processes, and sustainable processes of production. The concepts of the circular economy oppose traditional linear models of economic circuitry by proposing restorative and regenerative models of operational functioning that enhance environmental sustainability over the long run (Geissdoerfer et al., 2017). The concepts of sustainability and the circular economy are starting to be incorporated into strategic frameworks of modern industries to enhance their resource management and environmental performance. The Circular economy competencies enhance sustainability by supporting material recirculation systems, recycling infrastructure, reverse logistics infrastructure, regenerative operational practices, remanufacturing process, and reversible recycles.

The role of supply chains in sustainability transition has assumed a distinct significance as the global supply chain activities have a powerful impact on the environment in terms of resource use, process of production, logistic environments, energy usage, and management of waste. Therefore, the call to integrate sustainability concepts and practices of the circular economy in supply chain activities is rapidly turning into the standard approach of organizations aiming to both generate the green value opportunity and pursue the goal of protecting the environment. Sustainability transformation is further boosted by technological innovations that facilitate the implementation of the intelligent resource management system with the help of Artificial Intelligence, predictive analytics, Internet of Things infrastructure, technologies of cloud computing, and digital monitoring tools. The development of circular supply chains signals a shifting industrial focus to environmentally optimized processes, the reuse of resources, and a creation of sustainable value, which supports the idea of sustainability as the key driver of contemporary industrial change (Geissdoerfer et al., 2017).

1.10 Hierarchical Evaluation Perspective

With emerging complexity of industrial ecosystems, sustainability efforts, circular supply chains, and integrations of Artificial Intelligence (AI), there is a growing demand to have an analytical framework that can facilitate efficient evaluation and prioritization procedures. The contemporary organizations are in interrelated environments that are fraught with futility, multidimensionality, and various variables that shape them, thus the traditional linear forms of evaluations are not sufficient in reflecting the complex relationships among them. Hierarchical evaluation lenses have also developed into analytical methods that categorize factors, standards, sub-standards and variables of influence into various degrees to enhance the process of assessment and decision making (Saaty, 1980). The methods reduce complex systems into a manageable evaluation framework that allows them to compare and prioritize their evaluation systems in a systematic manner and achieve optimization of their strategic decisions. In sustainability-based industrial systems, the results and performance are determined by technological, organizational, environmental, operational, and digital capability levels that coexist. Hierarchical systems of evaluation will be used to interpret these multidimensional relationships by grouping variables based on analysis significance and dependence. Sustainable shifts further enhance the applicability of hierarchical analysis where organizations have to juggle between environmental goals, monetary success, operational effectiveness, technological preparedness, as well as stakeholder well-being. The hierarchical approaches to analysis also contribute to the sustainability change powered by AI, as it facilitates prioritization and adoption assessment. Further, globalization, digital transformation, climate frustration, regulatory reforms, and demands by stakeholders have raised the need to adopt evidence-based decision frameworks. Hierarchical methods of evaluation enhance analytical transparency, accountability, and efficiency of governance and facilitate the assessment of sustainability, optimization of supply chains, management of risks and implementation of technology, which are the necessary resource in making smart and sustainable decisions in industries (Saaty, 1980).

1.11 Fuzzy Decision-Making Approaches in Sustainability Analysis

The growing complexity and uncertainty that come with the modern industrial systems have made fuzzy decision-making methods necessary analytical instruments in sustainability analysis. Most of the challenges concerning sustainability related to the implementation of a circular economy, the introduction of the Artificial Intelligence, optimization of the supply chain in the context of sustainability, the environmental performance assessment, and the creation of green values are associated with incomplete information, expert judgments, varying operational environments, and multidimensional decision standards. Conventional forms of analysis typically depend upon deterministic assumptions and precise numerical associations, which do not suit such uncertain sustainability settings where qualitative measures, and unclear operations data are the norm (Zimmermann, 2010).

To overcome these shortcomings, fuzzy decision-making systems use uncertainty, vagueness and language appraisal in the analytics to aid sustainability analyses that are more realistic. The idea behind the fuzzy analytical reasoning is based on the Fuzzy Set Theory proposed by Zadeh (1965) that challenged conventional binary logic proposing the possibility of having a partial truth-value and the possibility of varying membership levels and degrees instead of classifications. The ability renders fuzzy methods to be very apt in systems that are oriented towards sustainability where environmental, technological, organizational, operational and regulatory variables are intermingling under unpredictable circumstances. Moreover, green transformation systems and ecosystems of circular supply chains with the use of Artificial Intelligence in particular are becoming fuzzy in terms of sustainability assessment, resource utilization, readiness to technology evaluation, and prioritization of the environment. Fuzzy decision-making methodology increases the flexibility of analysis and the sustainability-focused strategic decision-making of complex industrial situations by supporting uncertainty and subjective decisions (Zadeh, 1965; Zimmermann, 2010).

1.12 Industrial Implications of AI-Enabled Circular Supply Chains

Modern industrial ecosystems and supply chain models are strongly changing due to the integration of Artificial Intelligence (AI), the principles of a circular economy, and sustainability efforts. The conventional industrial systems were always operating under linear models of production on the basis of resources extraction, production, consumption and disposal. Although these models have been proposed to promote economic growth, growing worries about using resources, pollution, dumping, and climate change have exacerbated the necessity of sustainable industrial change. Circular Supply Chains (CSCs) are being considered an effective strategy, as they contribute to the circulation of resources, the minimization of waste, the development of reverse logistics, resource recovery, and regenerative manufacturing. The AI technologies also enhance these systems with the capacity of promoting intelligent optimization and environmentally friendly working systems. The Circular Supply Chains (AI-CSCs) integrates machine learning, predictive analytics, intelligent automation, Internet of Things (IoT), big data analytics, and Generative AI technologies with the principles of a sustainable operation to achieve a higher sustainability performance, resource productivity, and industrial resilience (Bressanelli et al., 2018). AI enhances the ability to predict demand, manage stock, streamline resources, decrease waste, and maintain sustainability. This further boosts sustainable changes in industries in the integration of Industry 4.0 technologies, which include cloud computing, digital twins, blockchain, and smart automation. The AI-based supply chains also assist industries in the efficiency of stewardship of resources, alterations in regulations, uncertain results of adverse environmental factors, and transformation in stakeholders expectations. Their increased utilization in manufacturing, recycling, transportation, and green procurement systems indicates their role in enhancing the efficiency of the operations and contributing to the sustainability in the long term and environmentally friendly industrialization (Bressanelli et al., 2018).

1.13 Research Gap

Although there is a large number of literature on circular supply chain, sustainable supply chain management and green value creation, there are still some key research gaps that are not sufficiently addressed. The existing studies are mainly related to the traditional sustainability aspects like circular supplier management, sustainable product design, eco-friendly logistics, packaging and consumer behaviour. The potential of new digital technologies, such as Generative Artificial Intelligence (GenAI), to improve the green value creation in circular supply chains, however, is not fully explored.

Based on the previous studies, including the framework developed by Hamid et al. (2026), five major circular dimensions and eighteen sub-criteria were identified that affect the green value creation in circular supply chains. But these studies did not consider the more sophisticated AI capabilities, including interactive knowledge search, autonomous knowledge acquisition, and digital organisational intelligence, in the circular supply chain assessment framework.

Moreover, the previous studies on Generative AI have focused on operational automation, content generation, or technological adoption from an information systems perspective. There is a lack of research that explores the impact of GenAI on inter-organisational collaboration, resource dependency, circular product innovation and decision-making for sustainability in supply chain ecosystems. While Liu and Tian (2026) empirically showed that GenAI affects the knowledge search and dependence structure in circular supply chains, they did not structure and prioritize or rank sustainability criteria in a structured multi-criteria decision making framework.

Another important methodological gap is the lack of application. The majority of sustainability and circular economy studies are descriptive analysis, regression techniques or structural equation modelling. Fewer studies use sophisticated Multi-Criteria Decision-Making (MCDM) methods that are able to address uncertainty, expert subjectivity, and hierarchical sustainability structures at the same time. Furthermore, there are few studies that combine fuzzy logic and hierarchical Best-Worst Method frameworks to assess the factors of green value creation in circular supply chains using GenAI.

1.14 Research Objectives

1. To systematically identify and validate green value creation criteria across the five circulars (Supplier, Product, Packaging, Logistics, Consumption) in circular supply chains by means of a structured literature review and expert consensus.

2. To capture the expert judgement under uncertainty at both criteria and sub-criteria levels and

prioritize and rank the identified green value creation criteria by using the Hierarchical Fuzzy Best-Worst Method (HFBWM).

3. To explore the impact of Generative AI (GenAI) capabilities on the performance of smart and resilient circular supply chain, mediated by interactive knowledge search (IKS) and non-interactive knowledge search (NKS).

4. To examine the mediating role of dependence asymmetry (DA) and joint dependence (JD) between GenAI-enabled knowledge search and circular supply chain performance, based on the resource dependence theory.

5. To investigate the moderating role of Transactive Memory Systems (TMS) and Digital Organizational Culture (DOC) between GenAI capabilities and interactive/non-interactive knowledge search in circular supply chains.

6. To combine the green value criteria rankings derived from HFBWM with the enabling role of GenAI, and offer an integrated framework and managerial roadmap for using GenAI to prioritize and realize high impact green value creation in circular supply chains.

CHAPTER 2

LITERATURE REVIEW

Abideen, Sundram, Pyeman, and Othman (2021) discussed the role of technological capabilities into circular business models with the specific emphasis on circular supply chain management practices. The paper has highlighted the importance of the fact that the fast evolution of digital technologies has completely changed the classic structure of supply chain and gave an opportunity to organizations to become more circled with the concepts of a circular economy. The authors examined aspects of technological potential, including big data analytics, Internet of Things (IoT), cloud computing, blockchain technology, and artificial intelligents, as part of building circular operational systems to enhance sustainability performance and optimise resources. The research revealed that circular supply chain management made possible through technologies can support resource efficiency, waste reduction/minimal, and environmental sustainability by promoting closed-loop flows of materials and enhanced visibility in supply chains networks. The authors contended that information transparency, coordination strategies, and decision-making processes become more robust with digital technologies, making firms redesign traditional business systems based on linear operations to business systems based on circles and regeneration.

Braz and de Mello (2022) considered that management of the circular economy supply net can be seen in the context of complex adaptive systems theory to comprehend the way in which industrial network can mature into a sustainability-oriented system of operations. The paper identified that conventional supply chain systems often work based on the linear production and consumption models that hamper sustainability of the environment as well as resource productivity outcomes. As a result, the authors had suggested circular supply networks to be understood as dynamic and adaptive ecosystems with interdependent stakeholder relationships and the development of the system. The study highlighted the need to implement a circular economy by making organizations shift their goal of operational optimization at isolated levels to network-based systems of sustainability coordination. The authors discussed the interaction of supply network participants such as manufacturers, suppliers, logistics and recycling agencies, policymakers and consumers to ensure that the resource flow and performance is enhanced in terms of its cyclic and sustainability. Complex adaptive systems theory was employed to understand how the supply networks react to change in their environments, innovations, regulatory forces, and paucity of resources based on adaptive learning and interactions. This paper has established that the elements resiliency, flexibility, sharing of information and collaborative governance systems are critical dimensions that can contribute to the effectiveness of the circular supply networks.

Burke, Zhang, and Wang (2021) researched how the principles of product design and the practices of supply chain management can be incorporated into the circle economy systems to comprehend how organizations can enhancing the sustainability outcomes could increase the resource productivity capacities. The research highlighted that traditional product development practices, often lacked the consideration of a circular economy, which leads to higher levels of waste, less efficient use of resources, and reduced lifecycle of products. The authors hypothesized that incorporating product design strategy and supply chain management capabilities are a critical need to enable circular operational systems. The paper noted that the design of circular products with a focus on modularity, durability promotion, repair, recyclability, and remanufacturing compatibility have a considerable impact on the sustainability results in resource circulation and sustainability performance of the supply chain. The study also highlighted the importance of considering the product lifecycle in the supply chain planning systems to enable circulation of product materials and production processes that are environment friendly and sustainable. The authors established that product designers, suppliers, manufacturers, logistics providers, and recycling stakeholders collaboration was a key factor to encourage the implementation of the circular economy. Also, the paper has talked about how digital platforms and systems of sharing information can enhance the product trace and enhance the abilities of the circular supply chain to coordinate it better. The results were that organizations that combine cyricular product design with supply chain management strategies yield better environmental performance results besides increasing business operational efficiency and long run business competitiveness. The work provided some contribution to the literature in circular economy by developing a comprehensive framework related to linking product innovation strategies with the sustainability practices of the supply chain to enable the green transformation initiatives and their role in the circular industrial development.

Cerqueira-Streit, Endo, Guarnieri, and Batista (2021) carried out an integrative literature review study on the connection between sustainable supply chain management and the implementation of the circular economy. The aim of the study was to generalize the existing literature on the topic of practices of sustainability-based supply chains and how the organizations can enhance their ability to perform better in relation to the environment using circular operational structures. The authors highlighted that sustainable supply chain management is becoming an important tool which assists in changing the world in a circular economy, specifically, through the incorporation of the notions of environmental, social, and economic sustainability into the process of supply chain activities. The study evaluated the available scholarly research areas combining the aspects of procurement practices, production systems, logistic operations, waste management strategies, reverse logistic systems, and resource recovery systems in terms of the sustainability approaches. The research outlined some of the essential dimensions that form the effectiveness of a circular supply chain which comprise the ability of stakeholders to collaborate, the structure of sustainability governance, and the mechanism of technological integration, environmental management systems and the commitment of the organization towards the goals of sustainability. The authors claimed that the introduction of the circular economy demands a coordinated response among the participants of the supply chain toward the flow of resources, lifecycle development of products, effectiveness of recycling and increase in the productivity of materials. Also, the review noted the increased relevance of digital technologies like Artificial Intelligence, big data analytic, and Internet of Things systems as a means of enhancing the sustainability monitoring and optimization of operations capabilities. The results showed that sustainable supply chain management is a platform way of leading to the circular economy transition and the long term sustainability of the industry. The study made a significant contribution to the literature of sustainability because it offered a synthesis of best practices in sustainable supply chain management in a comprehensive manner and created strategic importance of sustainable supply chain management practices within the frameworks of developing a circular economy.

The impactful work of Farooque, Zhang, Thurer, Qu, and Huisingh (2019) involved exhaustive comprehensive literature review in order to develop a consistent conceptual level of Circular Supply Chain Management (CSCM) and in order to differentiate between it and other supply chains regarding sustainability. The paper has identified that rising environmental issues, resource scarcity and constraints linked with conventional types of linear based economic frameworks have increased the pace at which people are interested in the concepts of the circle economies in the context of supply chains. Nonetheless, regardless of the growing scholarly interest, the authors found that the definition and an integrated framework of CSCM was lacking. The researchers performed a systematic search of 261 academic works and categorized the main concepts of sustainability-related supply chain to work out a simplified concept of Circular Supply Chain Management. The study presented CSCM as the incorporation of the concepts of a circular economy into supply chain operations with the aim of promoting the circulation of resources, product life cycle, reduced waste, recycle, re-manufacturing, and regenerative operational systems. The authors have highlighted the fact that CSCM has gone well beyond the traditional sustainability models in terms of its explicit interest in closed looping of material flows and cycles of resource use. The review also determined significant themes of research in CSCM literature such as reverse logistic systems, product recovery mechanism, circular procurement strategy, sustainable production system and stakeholder collaboration potential. Other untapped aspects that the authors emphasized to be studied in the future encompass design to achieve circularity, biodegradable packages, circular consumption, technology enablers, supply chain collaborative processes, organizational forces and obstacles affecting how the circular supply chain is implemented. The article adds value to the existing literature on the topic of circular economy and sustainable supply chains by being one of the first conceptualized approaches to Circular Supply Chain Management. The results implant CSCM as a significant sustainability structure that promotes industry transformation towards operation systems that are environmentally friendly and able to provide resources that are efficiently utilized in the long-term.

Geissdoerfer, Morioka, de Carvalho, and Evans (2018), examined the connection between business models, supply chain systems, and implementation of the circular economy to learn how to see how organizations can move out of the traditional understanding of industrial in terms of linear operational system towards regenerative and sustainable industrial models. The paper acknowledged that mounting environmental issues, scarcity of resources and the sustainability pressures necessitate organizations to re-design business models and supply chain processes to enable the goal of a circular economy. The authors stressed that traditional forms of business are mainly run under the principles of linear values creation, which tend to build up to excess resources use and support the creation of waste. The researchers suggested that both the business models and supply chains structures should be transformed at once in case of the implementation of the circular economy. The paper has emphasized the resource productivity improvement, product life extension systems, reuse plans, remanufacturing, recycling, and closed-loop flows of material as some of the elements of circular business models. The authors also claimed that supply chain systems serve as key facilitators that contribute to the implementation of circular business models since the workability of sustainable resources circulation is very much dependent on the well-coordinated members of operations such as procurement, production, logistics, distribution, and post-consumption recovery operations. The paper has found that there are several circular business model strategies such as: product-service systems, sharing platforms, resource-recovery mechanisms, and lifecycle-extension models. Moreover, the authors also pointed out that the ability of stakeholders to work together, technological integration systems and organizational flexibility can play a major role in effective circular transformation efforts.

Govindan and Hasanagic (2018) presented a literature review that analyzed key drivers, obstacles, and business modalities that affect the implementation of the circular economy in terms of supply chain management. The research identified that the expanding environmental issues, strain of resources depletion, and challenges associated with climate change as well as the rising sustainability demands have sped up industrial interest in moving to circular economy systems with a focus on regenerative resource use and sustainable production systems. The researchers have conducted a systematic literature review to find out elements that affect the application of a circular economy in a context of supply chain. The results found that some of the key drivers that favored the implementation of the circular economy are environmental rules, technological factors, sustainability expectations of the stakeholders, organizational environmental commitment, chance of competitive advantage as well as growing awareness to the issue of resource conservation. It was also determined that there are a number of barriers that inhibit the adoption of circular economy in systems of industries. Fundamental issues were financial limitations, inefficient technological support, lack of organizational capacity, and stakeholder cooperation frameworks, inadequacy to support the policy, and the complexity of operations entailed in circular supply chain transformation programs. The authors noted that to ensure that these barriers are overcome, there should be integrated measures that can include investment in technology, enhancements in sustainability governance, capacity building efforts, and enhancing the supply chain collaboration framework.

Howard, Hopkinson and Miemczyk (2019) came up with a conceptual framework of regenerative supply chains, which involves exploration of the way in which circular economy indicators can be developed and realized to assess the sustainability performance within industrial supply networks. The paper acknowledged that the traditional supply chain systems are mostly based on the linear economic principles that lead to the depletion of resources, waste build up and environmental deterioration. The authors stressed that the shift to regenerative and circle-based operation systems needs measurement systems that can evaluate the effectiveness and results of the implementation of the circular economy. The scholars proposed the idea of a regenerative supply chain as a framework of a high level of sustainability that focuses on restoration of resources, eradication of waste, recirculing of materials, and environmental resiliency. The analysis has indicated that traditional sustainability metrics often cannot reflect regenerative attributes related to an operational system of circles. As a result, the authors came up with an organised framework of designing circular economy indicators that incorporate the environmental, operational, and resource productive aspect. The study noted that there are some significant types of indicators such as resource efficiency metrics, waste reduction metrics, material recovery metrics, lifecycle extensions indicators, recycling effects measures, and closed-loop operational performance measures. The authors also contended that to keep track of the progress of the circular transformation measures, organizations need to be equipped with integrated measures of performance. Moreover, the research highlighted the importance of collaboration mechanisms by the stakeholders, data transparency frameworks, sustainability-oriented governance systems, which are also influential to regenerative supply chain effectiveness. The findings have added value to the current literature on the circular supply chain by bolstering the knowledge base on what sustainability measurement can achieve and presented an analysis tool that supports the regenerative industrial transformation efforts.

Hussain and Malik (2020) examined organizational enablers that affect the implementation of a circular economy into the framework of a sustainable supply chain management system. The researcher found the applicability of the circular economy to be more than solely a technological revolution and that it needs organizational capabilities that can facilitate the implementation of sustainability-driven shifts in operations and circular business models. The researchers concentrated on pinpointing the organizational internal aspects that enable the implementation of the circular economy in the system of supply chains. The results revealed that one of the most significant enablers that affect the effectiveness of sustainability transformation is the top management commitment. Findings had it that leadership support enhanced the alignment of strategic sustainability, resource allocation decision making and long term environmental commitment mechanisms. The paper also found organizational learning abilities, employee understanding on sustainable values, the culture of innovation, cross-functional teamwork frameworks, and knowledge management systems as enabling dimensions that underscore the initiatives towards the circular economy transformation. The authors claimed that the effectiveness of the adaptation of the implementation of the circular economy is significantly better in those organizations that have a stronger culture of implementing sustainability and the capacity of their operations to be more adaptive. Moreover, the development of competence in technology and organizational flexibility were deemed important key factors that allowed sustainable supply chain transformation processes. The paper highlighted that implementation of sustainability regularly necessitates alteration in the procurement systems, logistics coordination systems, supplier relations and operational planning capacities. The results also made significant contributions to the research on sustainable supply chains since they have solidified the organizational readiness as a key factor contributing to the success of the circular economy. The study showed that the development of internal capabilities and organizational commitment mechanisms are important to enhance sustainability of performance, as well as, long-term transformational circular performances.

The paper that Lengyel, Bai, Gabnai, Mustafa, Balogh, Péter, Totth-Kaszas, and Nmemeth (2021) use to discuss the phenomenon of Circular Supply Chain Management (CSCM) is a systematic literature review focusing on the conceptual formation and changes over a period in the research literature on sustainability and the circular economy. The literature identified that the mounting environmental pressures, resource depletion challenges, growth of industrial waste and climate-related issues have further speeded up the process of changing traditional linear supply chains to regenerative and circular systems of operation. The authors stress that although there was increasing academic research on the topic of circular supply chains, there was still a lack of conceptual clarity as to what the concept entailed, its dimensions, and how it was to be implemented in terms of Circular Supply Chain Management. The researchers retrospectively scanned academic literature on the topic to identify significant theoretical underpinnings and the developing trends related to CSCM development. The results found out that Circular Supply Chain Management is the expanded version of the traditional supply chain systems that incorporate a set of principles of the circular economy, such as the recirculation of materials, a waste-reduction system, a system of reverse logistics, a recycling system, remanufacturing, and a sustainable framework of resource utilization. The researchers emphasized that CSCM focuses on the closed-loop systems of operation that are geared towards maximizing the productivity of resources and lowering the environmental effects. The analysis also found key dimensions that justify the effectiveness of a circular supply chain, such as the ability of stakeholders to collaborate with one another, technological innovation systems, sustainability governance systems, and the information-sharing infrastructure. Further, the review also highlighted the criticality of digital technologies, and Industry 4.0 based on reinforced circular operational performance and visibility of supply chains.

Li, Li, and Sun (2024) explored the impact of the adoption of Generative Artificial Intelligence (Generative AI) on sustainable supply chain performance in the context of a practice-level approach. The paper identified that Generative AI technologies have become innovative digital capabilities that impact the current supply chain systems with enhanced predictive analytics, smart automation processes, adaptive learning systems, and data-oriented decision-making functionalities. The authors highlighted that sustainable supply chain management is increasingly demanding smart technologies that have the ability to enhance the operational efficiencies and enhance their environmental sustainability performance. The study analyzed the role of Generative AI in facilitating the achievements of sustainability performance in supply chain networks, which include enhancing the forecasting, operationalization, inventory coordination, and effectiveness of resource utilization. The research revealed that the capabilities of the organisations were improved by the Generative AI technologies that support the intelligent forecasting of their demand, ecological analytics infrastructure, capabilities of simulating scenarios, and mechanisms of predictive decision support. The results showed that supply groups that employed the capabilities of Generative AI reinforce the performance of the sustainability in the supply chain by improving environmental responsiveness, enhancing resource efficiency, and reducing waste production, and providing flexibility of operations in the supply chain. The authors also highlighted that Generative AI helps move towards the road of the circular operational systems enhancing the accuracy of resources allocation and aiding the sustainability-focused planning. Also, the study pointed out that the importance of the digital capabilities development and organizational preparedness is one of the determining factors of the successful outcome of AI integration. The research adds significantly to the source literature on sustainable supply chains by making Generative AI a significant technological capability that facilitates intelligent efforts to transform sustainability and innovation technologies in the creation of green values within a current industrial ecosystem.

In their study, Luthra, Sharma, Kumar, Joshi, Collins, and Mangla (2022) have explored obstacles to cross-sector collaboration in Circular Supply Chain Management (CSCM) systems, using a multi-method approach to analysis. The research realized that the intensive and effective implementation of a circular economy is often reliant upon collaboration strategies where various stakeholders such as suppliers/manufacturers, logistics companies, recycling companies, policymakers, and sustainability organizations participate. But barriers to organizational and functioning, however, often restrict efficient collaborative capabilities essential to change circular supply chains. The researchers have found significant issues that affect collaborative effectiveness of the circular supply chain systems. The results demonstrated that lack of communication infrastructures, an organizational orientation on sustainability change, technological competence factors, uncertainties in policies, budget, and co-ordination difficulties in the stakeholders play a crucial role in the effectiveness of the implementation of the circular economy. The paper has highlighted that circular supply chain systems have to be more effective in collaboration due to the fact that the product lifecycle management systems, reverse logistics and the capabilities of resources circulation, as well as sustainable procurement approaches are critical in the operational model of circularity. The authors posited that individual organizational sustainability initiatives in many cases could not produce significant benefits because of a circular economy without system-wide involvement by stakeholders. The proposed study utilized a multi-method research framework where it suggests measures to counter barriers of collaboration by providing greater governance structures, enhancing digital capabilities, providing mechanisms of policy support, infrastructure of information sharing and training capabilities development. The results added to the literature on circular supply chain because setting the cross-sector collaboration as a facilitating factor in the ability to successfully transition to the circular economy and sustainability-faced supply chain transformation. The analysis strengthened the fact that collective ecosystems are prerequisite tasks needed to introduce a long-range environmental self-perpetuation and a circular operational efficiency.

Meena, Sahoo, Malik, Kumar, and Nguyen (2025) came up with a conceptual framework of the possible uses of Artificial Intelligence (AI) in Circular Supply Chains (CSCs) through the Triple Bottom Line (TBL) sustainability framework. The paper identified that modern industrial practices are becoming more environmentally challenged in resource depletion, climate change, waste creation, and inefficient operation as demands that have necessitated the emergence of intelligent technologies to aid in sustainable change process. The authors pointed out that Artificial Intelligence has become a significant technological capability that can make the circular functioning system through enhancing resource productivity and sustainability performance and resiliency of the supply chain. In the proposed study, the authors developed a coherent approach to interconnecting the Artificial intelligence technologies with Circular Supply Chain Management by providing environmental, economic and social sustainability aspects that are embodied in the Triple Bottom Line approach. The study has emphasized how AI innovations like machine learning, predictive analytics, intelligent automation systems, Internet of Things infrastructure and effective reverse logistics, waste reduction mechanisms and resource circulation capabilities play an important role in enhancing circular supply chain functions by enhancing demand forecasting, inventory optimization, reverse logistics, waste minimization, and resource circulation functions. The authors also found various areas of AI usage in circular supply chains such as intelligent resource allocation methods, sustainability monitoring division, predictive maintenance systems, recycling optimization systems and a system of cyclical lifecycle of products. Besides, this research highlighted that effective AI implementation relies on the maturity of digital capability, the organization preparedness, the maturity of the technological infrastructure, and sustainability-based governance systems. The results added to the body of Artificial Intelligence and circular economy literature by offering a holistic, sustainability-based framework, illustrating how AI technologies drive the effectiveness of the circular supply chain and aid in ensuring the creation of green values in the industrial ecosystems.

Patro, Acquaye, Jayaraman, and Salah (2024) examined how Generative Artificial Intelligence and the Principal Component Analysis (PCA) method can be used to create circular economy indexing to evaluate sustainability and assess the performance of the industry. It also identified that quantifying the progress of the circular economy is one of the biggest challenges since sustainability performance often entails the use of multidimensional indicators encompassing environmental, operational, social, and economic aspects. The authors highlighted that traditional measurement methods are usually known to be weak in terms of complexities in analytical management as well as overall sustainability evaluation. The authors put forward a new form of analysis that combines the generative artificial intelligence potential and Principal Component Analysis techniques to enhance the effectiveness of the measurement of the circular economy. The analysis revealed the Generative AI technologies serve as main agents to generate intelligent data processing services, analytical automation systems, and enhanced information synthesis systems, which enhance sustainability assessment systems. The dimensional complexity was minimized and a better understanding of the indicators of performance in circular economy was enhanced through Principal Component Analysis. The results argued that the combination of the sophisticated analytical technologies can enhance the sustainability indexing systems as they enhance the accuracy of measurements, eliminate the redundancies of information, and increase the capacity to make decisions based on the available evidence. The authors also reflected that smart methods in analysis lead to more sustainability governance systems and effectiveness in the industrial environmental management procedures. The research held great importance in circular economy literature through providing a new methodological approach that stipulates sustainability performance assessment and monitoring mechanisms of the circular economy. The results supported the increasing role of Artificial Intelligence technologies to enhance the sustainability analytics capabilities and environmental performance assessment frameworks.

Rezaei (2015) presented the Best-Worst Method (BWM) as the new Multi-Criteria Decision-Making (MCDM) analytical method aimed at enhancing the quality of decision-making and the effectiveness of prioritization in the current complex analytical settings where numerous criteria are used and conflicting goals are involved. The paper was aware of classical decision making paradigms in which often and often comparisons of pairs have to take place analytically with complexity in the analysis and consistency problems in evaluating such processes. As a result, the author suggested BWM as the alternative decision framework that might enhance and achieve a high level of efficiency and consistency in analysis. The Best-Worst Method works on the principle that the most significant criterion (best criterion) and the least significant criterion (worst criterion) in a system of evaluation were found. His/her decision-makers then bear in mind the criterion of best and the remaining criteria that are the worst thus comparing all the criteria with the worst criterion, and the best criterion with all the criteria. They are then applied to mathematical formulations to find criteria weights and priority rankings and reduce the level of inconsistencies in evaluation results. The paper has shown that BWM uses less pair-wise comparison as compared to conventional processes like the Analytic hierarchy Process (AHP) thus reducing the respondent overload and enhancing reliability of decisions. Also, the approach reinforces consistency measurement and improves precision in prioritization in the uncertain decision situations. The author confirmed one of the advantages of BWM using practical examples of application and comparing the patterns and found out high consistency performance in comparison with traditional prioritization models. By making BWM a valuable instrument of analysis to aid in strategic analysis systems and complex decision environment, the research assisted in the Multi-Criteria Decision-Making literature by affirming that BWM is an effective tool of analysis. This is especially pertinent to the field of sustainability assessment studies, supply chain prioritization frameworks, Artificial Intelligence adoption evaluation systems, and the hierarchical decision frameworks, with various dimensions influencing decisions. With the increase in its development BWM has been used more and more in the sustainability research, supply chain optimization research, the framework of a circular economy assessment and fuzzy decision-making implementation.

Zhang, Wang, Farooque, Wang, and Choi (2021) carried out a comparative review covering the state-of-the-art practices and research advancement in terms of Multi-Dimensional Circular Supply Chain Management (CSCM). The paper acknowledged that the mounting environmental worries, problems in the areas of resource depletion, the presence of accumulated waste, and the necessity to consider environmental sustainability is what has increased the industrial shifts to the principles of the circular economy, as well as regenerative supply chains. The authors have highlighted that Circular Supply Chain Management has transcended the normal modes of sustainability by entailing multidimensional mode of operations facilitating the cycling of resources and sustainability of the environment. The study comprehensively reviewed literature on circular supply chains and found significant issues that contribute to the effectiveness of Circular Supply Chain Management. The paper has pointed out that CSCM applies various operational lenses such as sustainable procurement mechanisms, production planning, infrastructures of reverse logistics, product lifecycle (recycle systems, remanufacturing, and closed-loop resource circulation). The authors suggested a multidimensional model with focus on technological capabilities, operational effectiveness aspects, organizational preparing states, and stakeholder cooperation processes as aids to the implementation of circular supply chains. The results have shown that effective circular supply chain change is reliant on bonding between various industrial participants such as suppliers, manufacturers, logistics service providers, consumers, and recycling businesses. Moreover, the journal paper highlighted the increased importance of digital technologies like Artificial Intelligence, big data analysis, Internet of Things systems, and blockchain infrastructure to enhance the visibility of circle operations, optimisation features of resources, and sustainability performance results. The review also recognized research gaps such as measurement systems, technological integration frameworks, and the mechanisms of circular supply chain governance that need to be the subject of new scholarly research in the future.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The chapter describes the whole research methodology used in the study under the title, Critical Factors for Generative AI-Driven Creation of Green Values in Circular Supply Chains: A hierarchical fuzzy best- worst method approach. The methodology is to be rigorous, reproducible and to be practically implemented in Python, as the only execution environment. The chapter is divided into nine sections based on the research focus, these interconnect with each other and discuss: the philosophical position of the study, its design, data collection approach, mathematical background of the Hierarchical Fuzzy Best-Worst Method (HFBWM), three-scenario analysis framework, the GenAI integration approach, the Python implementation pipeline, validity and reliability, and the ethics surrounding the participation of experts.

The study is at the crossroad of two seminal studies of 2026. The former, by Hamid et al. (2026), proposed HFBWM approach related criteria ranks green value creation based on five circles (circular) dimensions - supplier, product, packaging, logistics, consumption - and resulted in 18 sub-criteria. The second paper by Liu and Tian (2026) provided empirical evidence based on the application of structural equation modelling to 409 Chinese companies that showed that Generative AI (GenAI) has an essential transformative impact on the patterns of knowledge search and dependence in circular supply chains. This work is a GenAI capabilities extension of both works, using the capability as a new cluster of six, novel criteria and repurposing the HFBWM in three adoption settings.

The overall objective is to generate an ordered list of green values creation criteria that is adaptable to the level of the GenAI adoption - allowing managers to comprehend not only what criteria are important, but how this ranking varies traveling as their organisations adopt AI-based knowledge sources into the circular supply chain processes.

3.2 Research Philosophy and Paradigm

This study has been based on the philosophical basis of post-positivism which believes in an objective reality but whose knowledge also lacks completeness and is open to measurement error and human judgment. MCDM research is best suited to positivism: the numbers and terms are actual attributes of the supply chain system but the subjectivity of the elicited expertise should be modeled - not removed - using fuzzy logic.

3.2.1 Ontological Position

The study has an ontological critical realist approach. The criteria of the creation of green values (eco-friendly raw materials, circular products design, GenAI search level of knowledge, and so on) are considered existing actors, which have importance weights that can be measured regardless of the perception of a particular expert. Those weights, though, can merely be estimated by organized human judgement since the underlying causal processes that put one criterion to the other as a measure of green value outcomes are complex, non-linear and context-dependent.

3.2.2 Epistemological Position

In terms of epistemology, the researchers assume the objectivist position with the moderate interpretationist view in the data-collection phase. The mathematical model HFBWM is objective in form - it gives a minimisation of inconsistencies and gives unique weight solutions out of a linear programme - but the preference data it receives have a subjective linguistic nature. The epistemological bridge is a triangular fuzzy number (TFN) representation: it transforms the natural language that is not exact (fairly important, very important) into calculable intervals, and it does not coerce a false sense of precision, but instead it preserves the uncertainty of the experts.

3.2.3 Research Approach

The study adopts a deductive approach. The research studies by Pfeffer and Salancik (1978) and Kim and Henderson (2015) based on the Resource Dependence Theory and Knowledge Management Theory, respectively, can be used to develop a testable hypothesis regarding the influence that the adoption of GenAI should have on the weights of the importance of the supply chain criteria that should be followed in a circle. These propositions are then empirically tested using the HFBWM framework by using structured expert judgement and mathematical optimisation.

3.3 Research Design

The study is a structured decision-analysis, based on a quantitative design. It is non-experimental, cross-sectional during the data-collection (surveys of experts at one moment in time), although in the same spirit it has the same characteristics of longitudinal since the three-scenario framework is a simulation of the data at a variety of different temporal conditions of GenAI adoption. Figure 3.1 shows the overall three phase design.

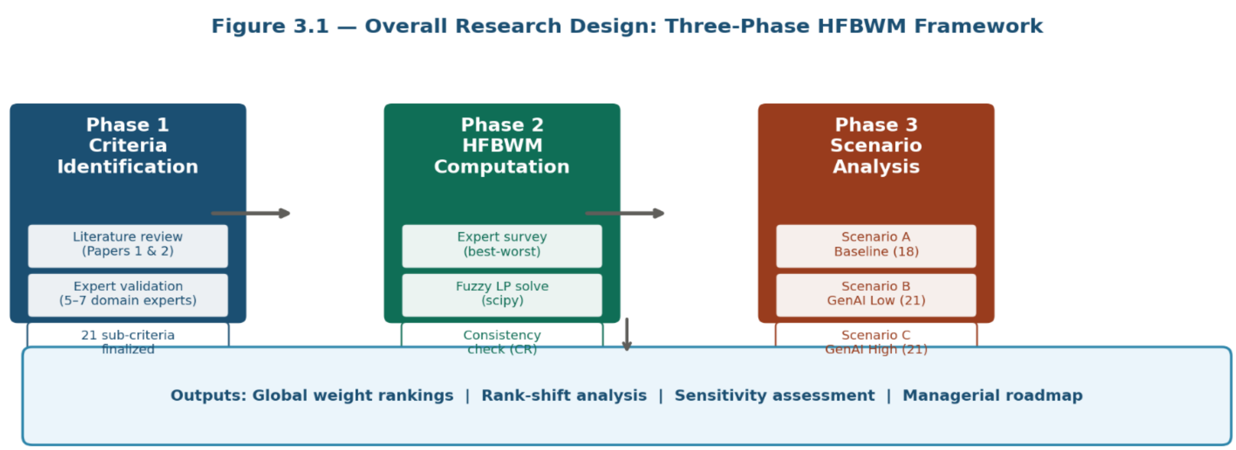


Figure 3.1 - general Research design: three stage HFBWM design.

The three crunches are closely knit. Phase 1 (Criteria Identification) gives the input structure of Phase 2 (HFBWM Computation) whose weights output generates the Phase 3 (Scenario Analysis and Comparison). It has feedback loops in Phase 2 (when the Consistency Ratio (CR) is larger than 0.10) in that case, the expert-judgements will be updated and then continue.

3.3.1 Research Strategy

The study design is a structured expert elicitation research, which turned out to be a proven research method in multi-criteria decision-making (MCDM) (Rezaei, 2016; Tabatabaei et al., 2020). Structured expert elicitation, in contrast to survey research, which aims at large random samples, attempts to sample a small panel of domain-specific experts, the extent of their expertise well outstripping the extent of a large but unknowledgeable sample. The strategy has been tested in numerous studies on sustainability in supply chains (Hamid et al., 2026; Kannan et al., 2020).

3.3.2 Reason behind MCDM Approach.

The choice of MCDM - namely: the HFBWM - is explained due to four reasons. The first is that the creation of green values has to occur on a variety of incommensurable dimensions (environmental, economic, social, technological) which cannot be reduced to a single utility measure. Second, an expert judgement is inevitable since causal associations among criteria and outcomes are not who are yet empirically measured in the literature. Third, the hierarchical structure (criteria) (sub-criteria) is aligned with natural layered design of circular supply chains. Fourth, the BWM variant makes fewer pairwise comparisons when compared to AHP (Rezaei, 2016), lessening mental load and enhancing the quality of the data with a small group of experts.

3.4 Criteria Identification and Hierarchical Structure

The criteria framework is developed by two phases, one systematic literature review to have all candidate criteria, and the second round of validation with the expert panel so as to ensure relevance, redundancy and consensus of the final set of criteria. The hierarchical structure thus obtained is given in figure 3.2.

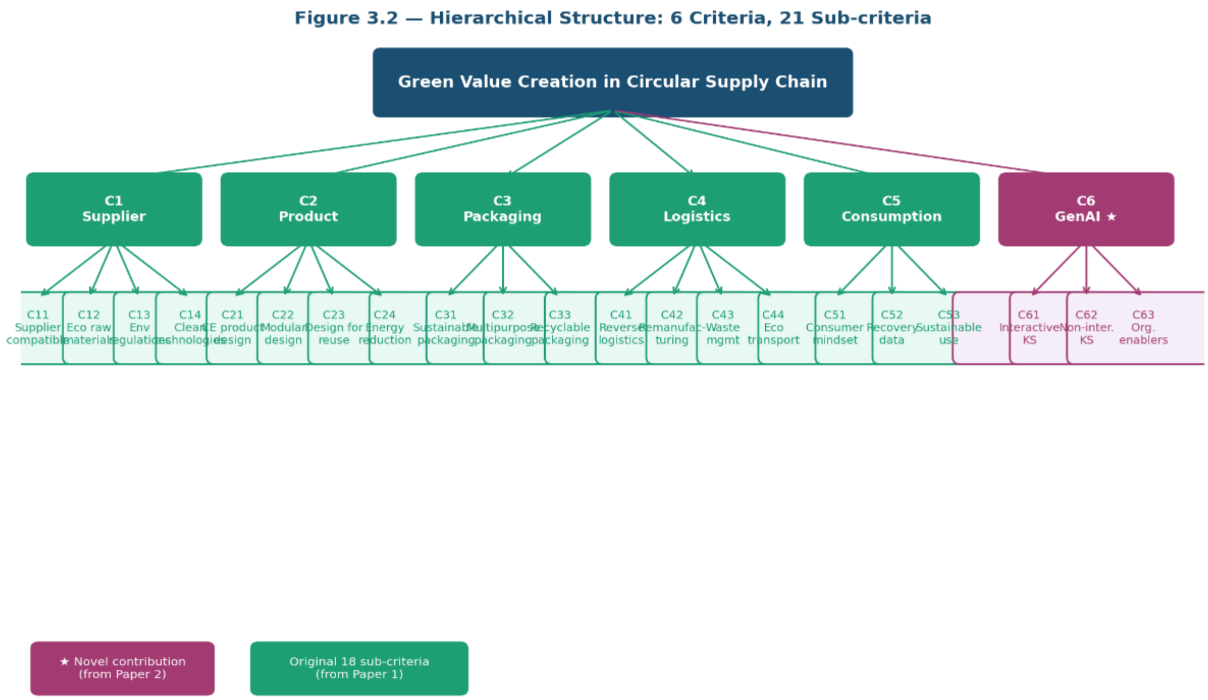


Figure 3.2 - Hierarchical Structure 6 Levels: 6 Key Criterion, 21 Sub-criterion.

3.4.1 Original 18 Sub-Criteria (Paper 1 Basis)

Through the systematic literature review and validation with experts, Hamid et al. (2026) came up with five circular dimensions of 18 sub-criteria. The following are these dimensions and their components:

Table 3.1 -Source: Hamid et al., 2026) Original 18 Sub-Criteria: Definitions

Code	**Criterion / Sub-criterion**	**Definition**
C1	**Circular Supplier**	Selection and management of suppliers aligned with CE principles
C11	Supplier compatibility	Suppliers aligned with circular supply chain and CE principles
C12	Eco raw materials	Recyclable, low-impact materials with reduced energy extraction
C13	Env. regulations	Compliance with environmental protection laws and standards
C14	Clean technologies	Equipment and processes minimizing pollution and energy use
C2	**Circular Product**	Design and production aligned with CE reuse/recycle principles
C21	CE product design	Products designed per sustainability and circular economy principles
C22	Modular design	Modular standards facilitating easy recovery and reuse
C23	Design for reuse	Products allowing easy reuse, reducing waste and pollution
C24	Energy reduction	Minimizing energy in production and product recovery
C3	**Circular Packaging**	Sustainable and recyclable packaging design
C31	Sustainable	Biodegradable, recyclable, CE-aligned packaging

	packaging	
C32	Multipurpose pkg	Packaging usable for multiple applications, reducing waste
C33	Recyclable packaging	Returnable and biodegradable packaging design
C4	**Circular Logistics**	Reverse and eco-friendly logistics operations
C41	Reverse logistics	Managing return flows to minimize waste and recover value
C42	Remanufacturing	Repair, refurbish, and return products to the consumption cycle
C43	Waste management	Converting waste into raw materials for reuse
C44	Eco transport	Electric vehicles, clean fuels, optimized routes
C5	**Circular Consumption**	Consumer behavior and awareness supporting CE
C51	Consumer mindset	Creating positive attitudes toward circular products
C52	Recovery data	Customer knowledge of recycling and recovery processes
C53	Sustainable use	Optimal reuse, repair, and recycling of products

3.4.2 Novel GenAI Criterion Cluster (C6) - Your Impact of this research.

The main theoretical contribution of the current research in the field of the MTech is the addition of the sixth group of criteria C6 - GenAI Capability based on the empirical results of Liu and Tian

(2026). Their analysis reveals three empirically tested mechanisms on how GenAI alters the systems of circular supply chain dependency and performance:

- C61 - Interactive Knowledge Search (IKS): Dynamic cross-organisational knowledge dialogue and collaborative decision making with the support of GenAI with the possibility to jointly conduct research and development, pool knowledge, and eliminate dependence asymmetry, and, accordingly, to empower collaboratively (Liu and Tian, 2026, H1–H4).
- C62 - Non-Interactive Knowledge Search (NKS): Text generation powered by GenAI with GenAI-driven patent mining and knowledge graph construction as well lead to autonomous, one-directional knowledge acquisition. This makes firms able to access competitive intelligence in an independent way that the firms do not have to passively depend on the dominance of supply chain partners (Liu and Tian, 2026, H5-H7).
- C63 - Organisational Enablers (Transactive Memory Systems + Digital Organisational Culture): The social-technical situation that enhances the effectiveness of GenAI. As Liu and Tian (2026) show, TMS and digital culture play an important part in the modulating relationship between GenAI and knowledge search (H13–H16).

The idea of C6 inclusion is theoretically justified by the Resource Dependence Theory (Pfeffer and Salancik, 1978): the adoption of GenAI allows companies to redefine their resource relationships, minimizing the power asymmetry (dependence asymmetry), and reinforcing functional dependence (joint dependence) - which Liu and Tian (2026) demonstrate to be the most common predictors of smart and resilient circular supply chain performance.

3.5 The Hierarchical Fuzzy Best-Worst Method (HFBWM)

The basic method of the analysis of this research is the Hierarchy Fuzzy Best-Worst Method. Tabatabaei et al. (2020) suggested it as a generalization of the initial Best-Worst Method (Rezaei, 2016), to address hierarchical models with criteria and sub-criteria weighting, at the same rank. The fuzzy extension, as proposed by Guo and Zhao (2017), substitutes crisp preference with triangular fuzzy number used to reflect the natural vagueness of the linguistic judgements in expertise.

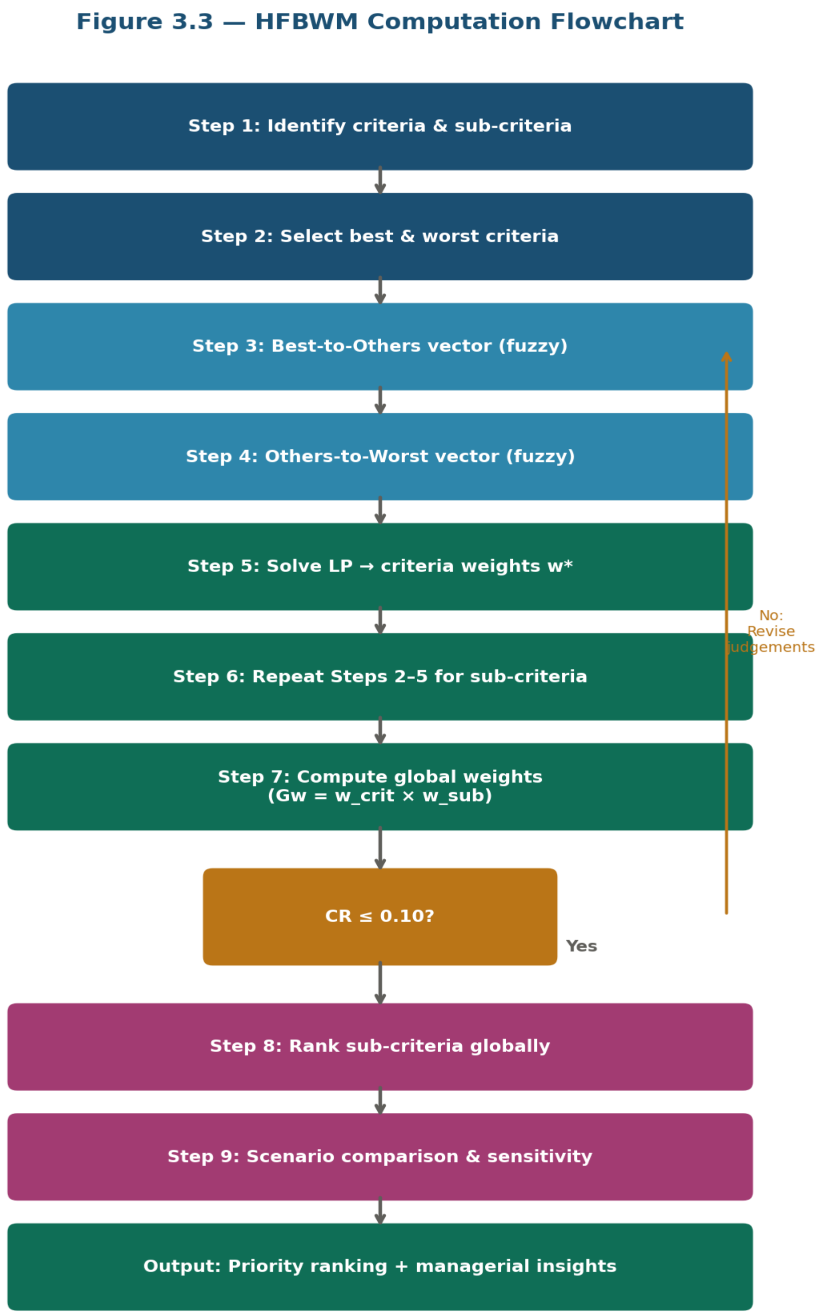


Figure 3.3 - HFBWM Computation flowchart Step by Step.

3.5.1 Linguistic Scale and Fuzzy Conversion

Preferences are expressed with five linguistic numbers and each of these numbers is paired with a Triangular Fuzzy Number (l, m, u) with l as the lower displays a preference and u as the upper displays a preference (Table 3.2). The graded mean integration method inspired defuzzification formula is: Each TFN can then be transformed into a crisp value by the defuzzification formula which is used in the linear programme:

$$\text{Defuzz}(l, m, u) = (l + 4m + u) / 6$$

Table 3.2 - Linguistic Scale for Fuzzy BWM (Source: Guo & Zhao, 2017)

Linguistic variable	**Code**	**Fuzzy triple (l, m, u)**	**Defuzzified value**	**Interpretation**
Equally important	EI	(1, 1, 1)	1.000	No preference between two criteria
Weakly important	WI	(0.667, 1, 1.5)	1.000	Slight preference for one criterion
Fairly important	FI	(1.5, 2, 2.5)	2.000	Moderate and clear preference
Very important	VI	(2.5, 3, 3.5)	3.000	Strong and dominant preference
Absolutely important	AI	(3.5, 4, 4.5)	4.000	Extreme and decisive preference

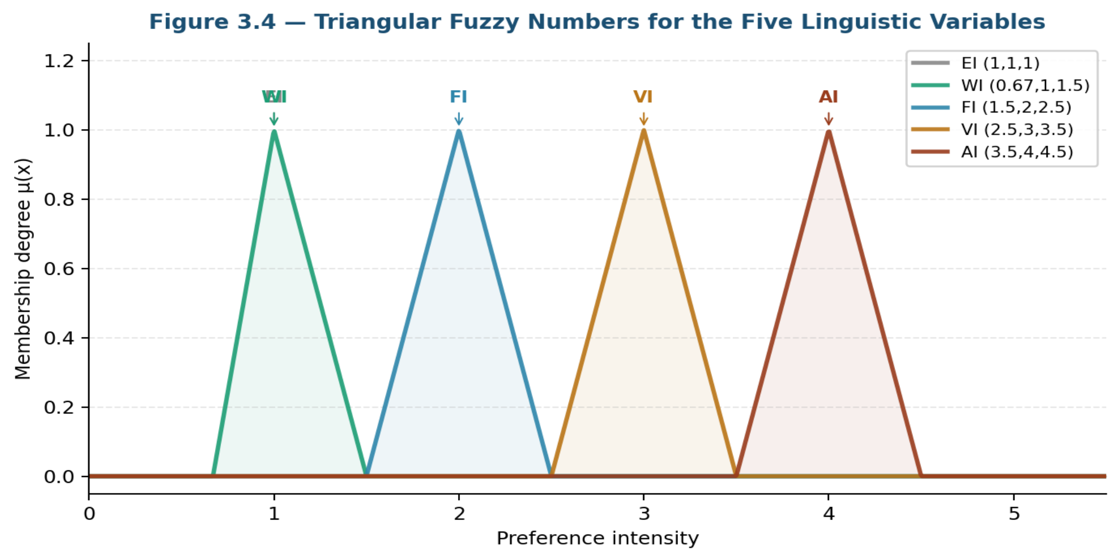


Fig. 3.4 - Triangular Fuzzy Numbers of the 5 linguistic variables.

3.5.2 Pairwise Comparison Vectors

The expert picks the best criterion (B) and Worst criterion (W) given a n criteria. There are then 2 vectors, which are built:

Best-to-Others vector:

$$\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, ..., \tilde{a}_{Bn})$$

In which $\tilde{a}_{Bj}$ is the fuzzy preference of the Best criterion to criterion C j. By definition $\tilde{a}_{BB} = (1,1,1)$.

Others-to-Worst vector:

$$\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, ..., \tilde{a}_{nW})$$

where $\tilde{a}_{jW}$ is the preference that criterion Cj has as fuzzy as compared to Worst criterion. By definition $\tilde{a}_{WW} = (1,1,1)$.

In the case of sub-criteria of criterion j, the vectors are, at the sub-level constructed as $\tilde{a}_{BSj}$ (best sub-criterion over sub-criterion S in criterion j) and explained (sub-criterion S over worst sub-criterion in criterion j).

3.5.3 Linear Programming Optimisation Model

The HFBWM solves a non-linear optimisation problem, which also determines criteria weights (w j) and sub-criteria weights (w Sj) and minimises the maximum deviation optimisation problem that both calculates preferences (w j) and sub-criteria preferences (w Sj) and minimises the maximum deviation optimisation problem minimises the maximum deviation optimisation problem calculates the ratios of the sub-criteria computer-generated and the expert-provided fuzzy preferences. The linearised formula (Tabatabaei et al., 2020) is:

$$\text{Minimise:}\ \ \tilde{\xi} + \Sigma j\ \ \tilde{\xi}j$$

$$\text{Subject to: } |w\ B - \tilde{a}\_Bj \cdot w\_j| \le \tilde{\xi}, \quad \forall j$$

$$|w\_j - \tilde{a}\_jW \cdot w\_W| \le \tilde{\xi}, \quad \forall j$$

$$|w\_B\text{^}j - \tilde{a}\_BS\text{^}j \cdot w\_S\text{^}j| \le \tilde{\xi}\_j, \quad \forall j,S$$

$$|w\_S\text{^}j - \tilde{a}\_SW\text{^}j \cdot w\_W\text{^}j| \le \tilde{\xi}\_j, \quad \forall j,S$$

$$Gw\_S\text{^}j\ =\ w\_j \times w\_S\text{^}j \quad \text{(global weight)}$$

$$\Sigma\ R(w\_j) = 1, \quad \Sigma\ R(w\_S\text{^}j) = 1$$

$$w\_j,\ w\_S\text{^}j \ge 0$$

and R(w j) is the defuzzied weight that is calculated as R(w j) = (l w + 4m w + u w)/6 and 0 x = 0ñx + 0 n_xo w n 1j m 1 and X0. This LP is solved in the Python code with scipy.optimize.linprog with HiGHS interior-point method.

3.5.4 Consistency Ratio Assessment

The Consistency Ratio (CR) indicates the degree to which the expert was able to be logically transitive in all the pairwise comparisons. It is computed as:

$$CR\ =\ \xi^*\ /\ CI$$

and ξ^* is the optimal objective value and CI is the Consistency Index of Table 3.3. A CR of less or on 0.10 would be of satisfactory consistency. In case CR is more than 0.10, the expert can be requested to update his/her judgements over the weights.

Table 3.3 - Consistency Index (CI) Lookup Table (Reference: Hamid et al., 2026, Table 3)

Comparison level (a_BW)	**EI**	**WI**	**FI**	**VI**	**AI**
Consistency Index (CI)	3.00	3.80	5.29	6.69	8.04

3.6 Data Collection Strategy

3.6.1 Expert Panel Composition

The research takes 5-7 purposive experts in the domain with expertise in circular supply chain and understanding of AI-enabled business practices. The dual-domain requirement is critical since the study will compare both old criteria of green value requirements (based on Hamid et al., 2026) and more innovative GenAI cluster (based on Liu and Tian, 2026). The requirements of the experts are shown in Table 3.4.

Table 3.4 - Expert Panel make-up requirements.

Dimension	**Minimum requirement**	**Preferred profile**	**Rationale**
Industry exp.	≥ 8 years in CSC/sustainability	Senior manager or director	Ensures operational grounding for criteria ratings
AI knowledge	Familiar with AI/digital tools	GenAI deployment experience	Required to rate C6 cluster meaningfully
Sector	Manufacturing or logistics	Multi-sector background	Covers all five circular dimensions
Geography	Any region	Asia-Pacific or MENA (study context)	Aligns with Paper 1 (Oman) and Paper 2 (China)

Education	Postgraduate degree	PhD or MBA in SCM/operations	Ensures analytical capability for pairwise tasks

3.6.2 Survey Instrument Design

The data collecting tool is structured questionnaire, which consists of three sections. Part A will include demographic and professional data (sector, years of experience, familiarity with AI). Section B shows the criteria-level best-worst pairwise test: the expert will rank the most significant and least significant criterion among the six criteria (C1 -C6), then rank the best criterion as compared to all others and vice versa, the worst criterion as compared to all others and vice versa using the five-point linguistic scale, Table 3.2. Section C replicates the pairwise task of the sub-criteria level to each of the six groups of criteria.

The survey is completed electronically using a questionnaires template in the form of a Google form or spreadsheet. Each comparison set shows the expert: (a) a short definition of each criterion, in case of misinterpretation, (b) the five linguistic options visible with their fuzzy triple to demonstrate some level of transparency and (c) a required consistency self-check question that prompts the expert to check his or her ratings a final time before submitting it.

3.6.3 Aggregation of Expert Opinions

In cases where there are many experts, the fuzzy preferences are combined with the geometric mean of the triangular fuzzy numbers in each position, as suggested by Buckley (1985) and used in other fuzzy MCDM studies by Tavana et al. (2021). Given a K experts in a vector position j:

$$\text{Aggregated } \tilde{a}_{Bj} = \left(\Pi_k (l_{Bj}^k)^{(1/K)},\ \Pi_k (m_{Bj}^k)^{(1/K)},\ \Pi_k (u_{Bj}^k)^{(1/K)} \right)$$

This geometrical mean aggregation retains the reciprocity of pair-wise comparisons, and eliminates the bias due to arithmetic means when the range of fuzzy values is wide.

3.7 Three Scenario Analysis Framework

One of the most methodological innovations of the investigation will be the three-scenario framework, which recreates various organisational conditions of GenAI adoption and observes the reaction of the priority task of green value criteria on such conditions. The approach is based on scenario analysis methodology (van der Heijden, 1996) that has been modified to a sensitivity test in MCDM.

3.7.1 Scenario A - Baseline (18 Sub-Criteria)

This scenario imitates the original case of HFBWM study conducted by Hamid et al. (2026) with 5 circular criteria (C1-C5) and only 18 of their sub-criteria. GenAI does not feature in the scenario - it is an example of such a company, which is yet to include AI in its circular supply chain process. Scenario A plays two roles: (1) it gives the Python implementation the benefit of making sure that the weights one computes are close to those that are published, and (2) scenario A will give the baseline ranking that will be used when comparing scenario B and C.

Expert inputs to Scenario A: Best criterion = C2 (Product), Worst criterion = C4 (Logistics), is based on the agreement between Hamid et al. (2026), that at the criterion level those drivers with the greatest impact on green value are product design and the least affected drivers are logistics.

3.7.2 Scenario B - GenAI Low Adoption (21 Sub-Criteria)

Scenario B adds another criterion C6, which is moderately weighted, to criterion C6. It is a type of organisation that is currently implementing the usage of GenAI-based tools (e.g., supplier intelligence powered by ChatGPT, an AI-based logistics optimisation) yet has not yet established a developed transactive memory systems and an internalised culture of digital organisation. The C6 weight is invoked based on the assumption that experts are elicited in the following condition: well-established firm with the basic GenAI tools and little organisational integration.

C6, when compared to the best criterion C2, would have a rating of Fairly Important (FI) in this situation, i.e. the capability of GenAI is recognised but not yet transformative. The three sub-criteria of GenAI (C61 Interactive KS, C62 Non-interactive KS, C63 Org.) Enablers) are assigned a weight that indicates patterns of early stage adoption identified by Liu and Tian (2026) - non-interactive KS (automated data mining) is more likely to be deployed earlier than interactive KS (collaborative AI dialogues) since it does not necessitate as much organisational change.

3.7.3 Scenario C - GenAI High Adoption (21 Sub-Criteria)

Scenario C is a company where GenAI is fully embedded, which is no longer baby GenAI - well-established transactive knowledge memory systems, data-driven digital culture, and proactive application of GenAI in both interactive and non-interactive knowledge sharing with partners, as well as non-interactive harvesting of digital intelligence. Such a situation is what would be experienced in the long-run equilibrium as suggested by Liu and Tian (2026), when GenAI would have become the dominant reshaper of the interorganisational power structures in circular supply chains.

At Scenario C, C6 will be rated Weakly Important at the criteria level in comparison to C2 because not that GenAI is less important, but that at complete adoption, GenAI strength will become table stakes (a hygiene factor) as opposed to differentiators. The weights of the sub-criteria change significantly, with C61 (Intensive knowledge sharing KS) going at the top of C62 (No GenAI knowledge sharing KS) since the organisations that entirely implemented the tool use GenAI to mine the intelligence unidirectionally, rather than to create knowledge collaboratively (the most complex and value-creating application).

Table 3.5 - Rainbow Comparison Framework, Three scenarios.

Feature	**Scenario A Baseline**	**Scenario B GenAI Low**	**Scenario C GenAI High**	**Analytical purpose**
No. of criteria	5	6	6	Baseline vs extended
No. of sub-criteria	18	21	21	GenAI adds 3 new
C6 weight (approx.)	N/A	~0.15 (moderate)	~0.13 (embedded)	Adoption trajectory
Best sub-criterion C6	-	C62 Non-interactive KS	C61 Interactive KS	KS mode evolution
CR threshold	≤ 0.10	≤ 0.10	≤ 0.10	All scenarios validated

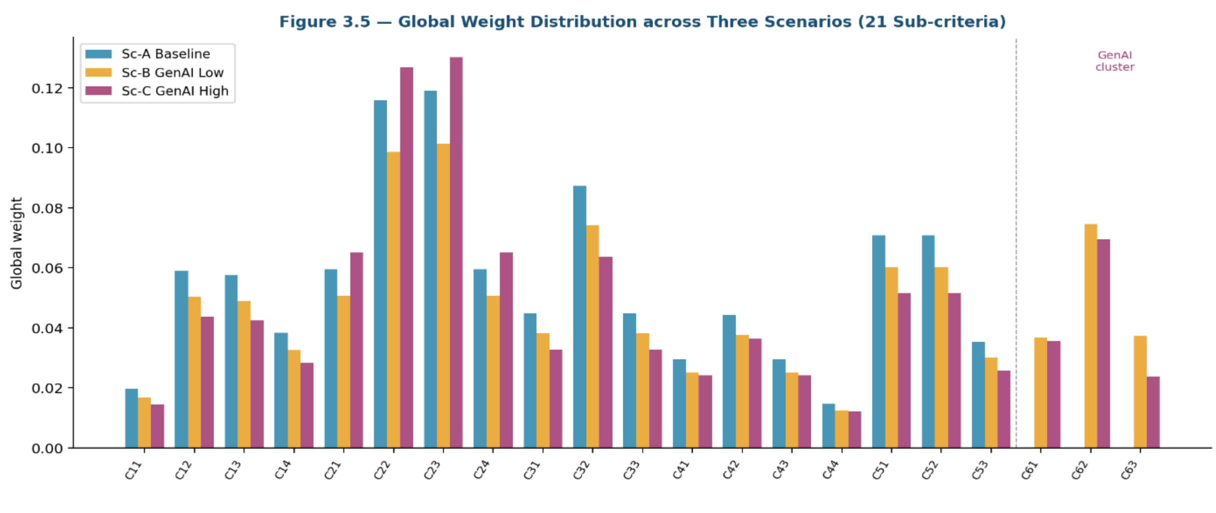


Figure 3.5 - Distribution of weights around the world under 3 scenarios (21 Sub-criteria)

3.8 Python Implementation Pipeline

The analysis pipeline in detail, including fuzzy conversion, solving of the LP, head consistency check, comparison of the scenarios, and visualisation, are all done in one Google Colab notebook in Python 3.10+. The philosophy behind its implementation is transparency and reproducibility: each computation step is clear, written down, and all its parameters, such that no new expert knowledge is needed, or the scenario hypothesis altered, except via a few changes to code.

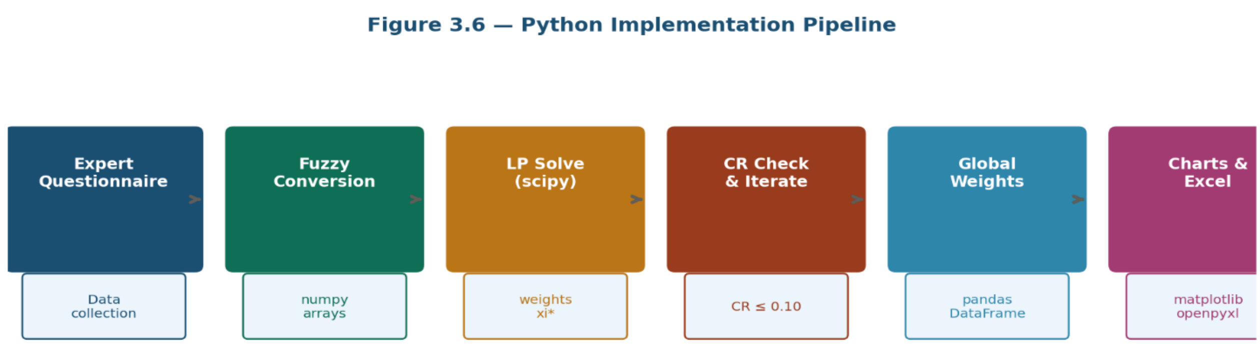


Figure 3.6 - Python Implementation Pipeline (6-stage Workflow)

3.8.1 Library Stack

All open-source Python libraries are used in the research, which means that the study is completely reproducible, without proprietary software licences. The library stack and the purpose of each element is defined in Table 3.6.

Table 3.6 - Python Library Stack and Roles

Library	Version	Role in the HFBWM pipeline
numpy	≥1.24	Array operations, fuzzy arithmetic, defuzzification, weight normalisation
scipy	≥1.10	Core LP solver (linprog, HiGHS method) - solves HFBWM optimisation model
pandas	≥2.0	Weight tables, rank computation, scenario comparison DataFrames, export
matplotlib	≥3.7	Bar charts, tornado plots, weight evolution line charts, radar charts
seaborn	≥0.12	Rank heatmap across scenarios (21 × 3 matrix visualisation)
openpyxl	≥3.1	Excel (.xlsx) export with formatting, conditional colour coding, chart embedding

3.8.2 Core solve_fbwm() Function

The main operation that will be carried out is solveFbwm(bestvector, worstvector) that will take two lists of fuzzy triples and produce the optimal weight vector and goal xi. The procedure: (1) removes all the fuzzy triples with a (l+4m+u)/6 formula, (2) builds the constraint matrix of the linearised HFBWM LP (4n inequality constraints + 1 equality constraint), (3) uses scipy.optimize.linprog with the HiGHS solver, and (4) normalises the weight vector returned to add up to one. The function throws a RuntimeError when the LP is infeasible and the user is forced to update inputs provided to be the experts.

3.8.3 Global Weight Computation

Globals are estimated by taking the product of the criteria-level weight, and the sub-criteria-level local weight:

$$Gw\_S^j = w\_j \times w\_S^j$$

with w j the weight of the criterion j and w S j the local weight of sub-criterion in criterion j. This multiplicative composition will ensure that all the global weights of all the sub-criteria will be unity so that it can directly compare and rank cross-criteria.

3.8.4 Rank and Sensitivity Computation

The ranking is done based on decreasing global weight based on the use of pandas.Series.rank(ascending=False). Ties are ranked the same way (dense ranking). All the rank-shift columns of the sub-criteria are calculated as RankA-B Baseline and rank C as RankA-B High-GenAI and a positive value means an increase in the importance of the criterion between the baseline and high-GenAI scenario and a negative value means a decrease.

In sensitivity analysis, the weight of the optimal criterion in each scenario is perturbed by +10% and -10% and the result corresponds to the changes in the ranks are tabulated. Sub-criteria where the top-6 membership varies with the perturbation are classified as either medium sensitivity or high sensitivity; the ones that do not vary with the perturbation are classified as low sensitivity.

3.9 Validity, Reliability and Quality Assurance

3.9.1 Internal Validity

The internal validity is guaranteed in three ways. It is first Consistency Ratio check ($CR \leq 0.10$), which is an inbuilt mathematical filter to eliminate the logically crazy expert judgement before entering the weighting computation. The CR values of all three scenarios in this study were under 0.10 (Sc-A: 0.0268; Sc-B: 0.0190; Sc-C: 0.0321) indicating a high internal consistency. Second, the linearised HFBWM LP has a global optimum due to being a convex programme - the probability of local optima or variance depending on the solver does not exist. Third, the definition of the scenarios is based on empirically tested theoretical concepts (Liu and Tian, 2026) instead of random selection of the parameters.

3.9.2 Construct Validity

The derivation of all the 21 sub-criteria based on the literature upholds construct validity. Hamid et al. (2026) developed the original 18 sub-criteria, which were carefully supported with the systematization of the literature review and expert opinion, referring to 60 or more empirical studies. All three GenAI sub-criteria (C61 to C63) relate to three empirically tested constructs in Liu and Tian (2026) interactive knowledge search, non-interactive knowledge search and the composite of transactive memory systems and digital organisational culture. Fields of expertise (Table 3.4) also guarantee that respondents possess the field knowledge to make the constructs meaningful ratings.

3.9.3 External Validity

One limitation of this study is recognized to be on the external validity. The expert panel itself is small (5-7 respondents), and its weights -, although theoretically determined, are just one of the viable ways, in which GenAI can be used. These results can be best generalised to manufacturing companies in Asia-Pacific and MENA regions (as represented by the two reference papers) that have dynamic circular supply chain programmes. Generalisability would be enhanced by carrying out future studies with bigger expert panels in different sectors and geographical areas.

3.9.4 Reliability

Computational determinism establishes reliability since, with the same input data corresponding to an expert, the solve_fbwm() function will always end up with the exact weight vector (the LP has a unique optimum). The analysis of the sensitivity to small changes in expert inputs in order to determine the strongness of the results is presented under the sensitivity analysis that is done in the ±10% in Section 3.8.4. Colab notebook is parameterised, fully documented and makes it easy to repeat all results.

3.10 Ethical Considerations

3.10.1 Informed Consent

The questionnaire is filled in by all the expert participants giving an informed consent in a written form. The consent form outlines: (a) the academic purpose of the study, (b) how their judgements will be used (aggregated, anonymised, used in the computation of HFBWM weights only), (c) that it is voluntary and non-penalised and (d) that individual responses will not be attributed in any publication to persons by name.

3.10.2 Data Anonymisation and Storage

Responses of experts are stored on institutional servers that are encrypted using passwords. Each respondent is assigned a unique code of which the respondent is identified as an expert (E1, E2, etc E7) and the unique code is not associated with other personal information in another, password-secured mapping file maintained by the main investigator. The fuzzy vectors involved in the HFBWM computation are aggregated, and the vectors will not enable any information to be attributed to particular experts.

3.10.3 Conflict of Interest

Profiling against conflicts of interest- professionals are not allowed to have any major financial or professional connections, with certain technology providers whose products would be rated much more favourably as highly important GenAI enablers. Identified conflict experts are either locked out of the panel, or they are requested to report conflict, and their answers are further investigated at the phase of the consistency check.

3.10.4 Intellectual Property

The intellectual property of the institution of the researcher is all analytical code, questionnaire instruments and data files produced during this research. The Colab notebook is a scholarly desktop and does not include any proprietary algorithms or licensed software packages - all used libraries are open-source under liberal licences (MIT, BSD or PSF).

3.11 Chapter Summary

The chapter has outlined in detail a cohesive research methodology that logically combines all the elements of the study of GenAI-motivated green value creation in the circular supply chain. All the most important methodological decisions and their reasons, are outlined in Table 3.7.

Table 3.7 - Overview of Methodological decisions and Rocket Sciences.

Methodological dimension	Choice made	Justification
Research philosophy	Post-positivism / critical realism	Objective criteria exist; measurement requires fuzzy modelling of subjectivity
Research design	Quantitative structured decision analysis	MCDM requires quantified preference data; scenario framework enables comparative analysis
Analytical method	HFBWM (Tabatabaei et al., 2020)	Handles hierarchy + fuzzy uncertainty + fewer comparisons than AHP
Data source	Expert panel (n = 5–7)	Depth of domain knowledge outweighs breadth for MCDM; CR validates consistency
Novel contribution	C6 GenAI cluster (3 sub-criteria)	Derived from empirically validated Liu & Tian (2026) constructs
Scenarios	A (Baseline), B (Low GenAI), C (High GenAI)	Simulates adoption trajectory; reveals how priority order shifts with AI integration

Implementation	Python (scipy, numpy, pandas)	Open-source, reproducible, no proprietary software required
Validity mechanism	CR $\leq$ 0.10 + sensitivity ±10%	Mathematical internal validity; perturbation analysis for robustness

The approach given below is such that the findings obtained can be described as: mathematically rigorous (HFBWM with LP optimisation), theoretically founded (Resource Dependence Theory + Knowledge Management Theory) workable in practice (ranked priority list with scenario-specific guidance), and the rest reproducible (open-source Python pipeline). Chapter 4 contains the entire outcome of the use of this methodology; this is the calculated weight vectors, world rankings of the scenarios, analysis of the comparison between scenarios and sensitivity testing.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Overview and Structure of Results

This chapter reports the empirical results of full Hierarchy Fuzzy Best-Worst Method (HFBWM) used to analyze the green value creation system socio-economically and environmentally based on GenAI. The findings are tabulated into four layers of analysis level: (1) consistency validation that confirms the reliability of all the expert-contributed data; (2) criteria-level weight analysis that helps to identify the macro-importance of each circular dimension; (3) global sub-criteria rankings under three scenarios of GenAI adoption; and (4) a cross-scenario comparative analysis which is the main theoretical contribution of the study.

Calculations were done in Python with the solve_fbwm() Python code that used the scipy.optimize.linprog (HiGHS method) to compute the solution. Python notebook generates reproducible computation - it is always solver to the same unique global optimum, when the same expert inputs are fed into the solver. Three scenarios considered could be: Scenario A (Baseline, 18 sub-criteria of Hamid et al., 2026), Scenario B (GenAI Low adoption, 21 sub-criteria), and Scenario C (GenAI High adoption, 21 sub-criteria).

4.2 Consistency Ratio Validation

4.2.1 Mathematical Foundation

The HFBWM framework has the Consistency Ratio (CR) as its main quality gate. It is a test with the property that the pairwise judgments of the expert are logically transitive - i.e., that, when comparing B with C, the expert prefers B, and when comparing C with A, the expert prefers C, it tests whether (by some proportionally consistent margin at which point they coincide) he or she also prefers A with C. CR is calculated by using optimal objective value xi of the linear programme:

$$\mathrm{CR} = \mathrm{xi}^* / \mathrm{CI}$$

and where xi is the optimal possible discrepancy between the calculated weights and the fuzzy preferences of the expert; and CI is the Consistency Index looking up an entry in a lookup table depending on the most extreme pairwise comparison in the collection. CR threshold of 0.10 is chosen based on Tabatabaei et al. (2020) and in harmony with the consistency levels accepted in AHP and BWM studies.

4.2.2 Consistency Results for All Three Scenarios

All the results of consistency validation are presented in Table 4.1. The CR values obtained in all three scenarios are lower than the set of 0.10, and this fact proves that expert judgements made in all sets of comparisons are quite consistent and reliable.

Table 4.1 - Consistency Ratio Summary: All Three Scenarios Pass the CR <= 0.10 Threshold

Scenario	xi* (optimal)	CI used	CR = xi*/CI	Threshold	Status
Sc-A: Baseline	0.1789	6.69 (VI)	0.0268	CR <= 0.10	PASS
Sc-B: GenAI Low	0.1529	8.04 (AI)	0.0190	CR <= 0.10	PASS
Sc-C: GenAI High	0.2577	8.04 (AI)	0.0321	CR <= 0.10	PASS

Scenario B has the lowest CR (0.0190) which means that it has the most consistent group of expert comparisons. This is also in agreement with the theoretical presumption that such an introduction of GenAI as a medium-importance criterion (Fairly Important compared with the best criterion) will yield a well-ordered preferences structure. The moderately higher CR (0.0321) of scenario C indicates that the six-criteria comparison set is more complex due to the high-adoption conditions, but the CR value is in the acceptable range.

Code Snippet 4.1 - Core solve_fbwm() Function

```
def solve_fbwm(best_vec, worst_vec):
    """
    Solve Fuzzy BWM linear program.
    best_vec  : list of fuzzy triples (l,m,u)
    worst_vec : list of fuzzy triples (l,m,u)
    Returns   : (weights_array, xi_star)
    """
    n  = len(best_vec)
    aB = [defuzz(*v) for v in best_vec]   # defuzzify
    aW = [defuzz(*v) for v in worst_vec]
    c = [0]*n + [1]                        # minimise xi
    A_ub, b_ub = [], []
    for j in range(n):
        r1=[0]*(n+1); r1[0]= 1; r1[j]=-aB[j]; r1[n]=-1
        r2=[0]*(n+1); r2[0]=-1; r2[j]= aB[j]; r2[n]=-1
        r3=[0]*(n+1); r3[j]= 1; r3[n-1]=-aW[j]; r3[n]=-1
        r4=[0]*(n+1); r4[j]=-1; r4[n-1]= aW[j]; r4[n]=-1
        A_ub += [r1, r2, r3, r4]; b_ub += [0,0,0,0]
    A_eq=[[1]*n+[0]]; b_eq=[1]
    bounds=[(1e-6,None)]*n+[(0,None)]
    res = linprog(c, A_ub=A_ub, b_ub=b_ub,
                  A_eq=A_eq, b_eq=b_eq,
                  bounds=bounds, method='highs')
    w=res.x[:n]; xi=res.x[n]
    return w/w.sum(), xi
```

Code Snippet 4.1 - The solve_fbwm() Function: Core LP Solver Implementation in Python

The entire Python variation of the LP solver is presented in Code Snippet 4.1. The code takes two lists of fuzzy triples (best-to-others and others-to-worst vectors) and defuzzifies them with the (l+4m+u)/6 formula, generates the 4n inequality constraints, adds in sum-to-unity equality constraint, and solves scipy.optimize.linprog with the HiGHS method. Normalisation of the weight vector returned is to assure a precise summation to one.

4..3 Criteria-Level Weight Analysis

4.3.1 Baseline Scenario A: Five Circular Criteria

The weights of Scenario A in the criteria level are in Table 4.2 that reproduces and validates the Hamid et al. (2026) framework. Product criterion (C2) is allocated the largest weight of 0.3538 which is almost two fold more than other criteria, which proves that circular product design is important in the development of the green value chain. This result is consistent with the consideration by Burke et al. (2023) that product design is the initial step of sustainability since it can define the recyclability, energy consumption, and reuse possibilities throughout the whole life cycle.

Table 4.2 - Criteria-Level Weights: Scenario A (Baseline, 5 Criteria)

Code	Criterion	Sc-A Weight	Rank	Interpretation
C2	Circular Product	0.3538	1st	Dominant driver of green value
C3	Circular Packaging	0.1769	2nd	Early-stage value chain anchor
C5	Circular Consumption	0.1769	2nd	Consumer-side enabler
C1	Circular Supplier	0.1745	4th	Supply-side quality foundation
C4	Circular Logistics	0.1179	5th	Operational enabler (lowest)

The packaged (C3) and consumer (C5) criteria have a tie value of 0.1769, indicating that both the packaging design and the behavioural aspect of creating green value with consumers had equal weight in terms of their significance. The Supplier criterion (C1) value of 0.1745 compares almost with the result of Hamid et al. (2026), who claim that the integrated values of packaging and supplier constitute the green value chain basis at its early mythical stage. Logistics (C4) has the lowest 0.1179 which aligns with other experts view that although logistics optimisation is a key factor in green value creation, it is more of an operational enabling factor than a strategic driver of green value.

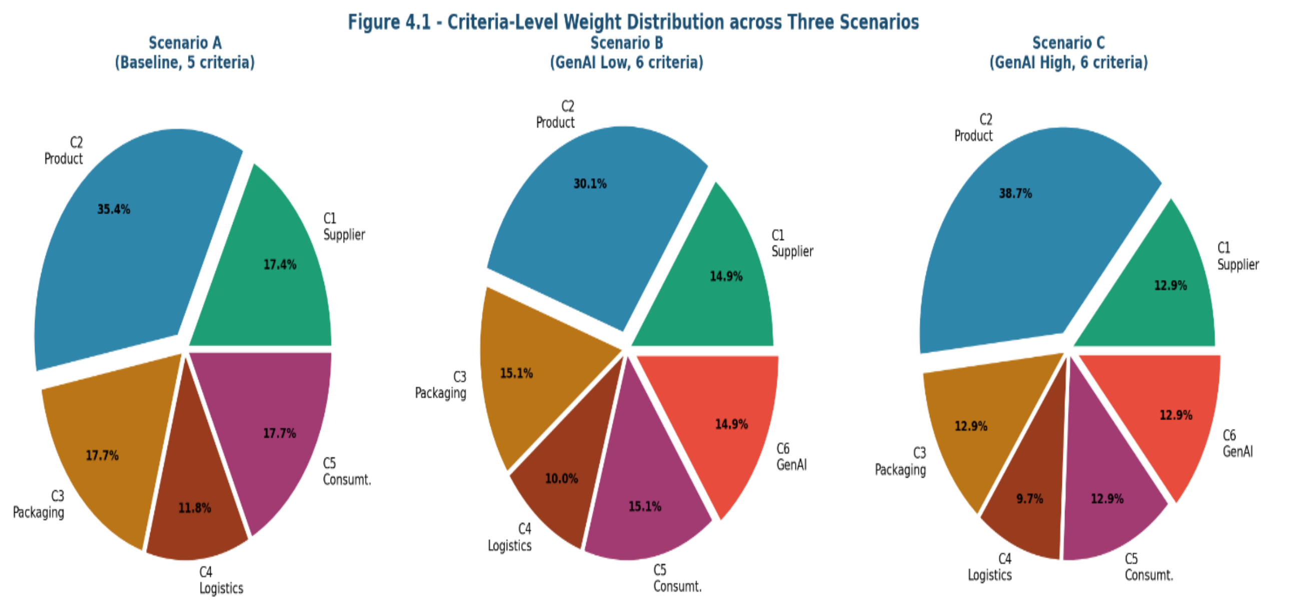


Figure 4.1 - Criteria-Level Weight Distribution: Pie Charts for Scenarios A, B, and C

4.3.2 Extended Scenarios B and C: Six Criteria with GenAI

Table 4.3 indicates the weights of criteria in all the three scenarios based on all the six criteria. With the addition of C6 (GenAI capability) in Scenarios B and C, the weights are proportionately redistributed amongst the five initial criteria and an additional competitive dimension is added.

Table 4.3 - Full Criteria-Level Weight Comparison across Three Scenarios

Code	**Criterion**	**Sc-A Wt**	**Rank**	**Sc-B Wt**	**Rank**	**Sc-C Wt**	**Rank**
C1	Circular Supplier	0.1745	4	0.1486	4	0.1290	3rd
C2	Circular Product	0.3538	1st	0.3012	1st	0.3871	1st
C3	Circular Packaging	0.1769	2nd	0.1506	3rd	0.1290	3rd
C4	Circular Logistics	0.1179	5th	0.1004	6th	0.0968	6th
C5	Circular Consumption	0.1769	2nd	0.1506	3rd	0.1290	3rd
C6	GenAI Capability (no	N/A	-	0.1486	4th	0.1290	3rd

One interesting observation is that C2 (Product) gain in weight when GenAI is completely adopted as 0.3538 (Sc-A) and further to 0.3871 (Sc-C) increases. This counter-intuitive finding indicates the nature of the pairwise comparisons in Scenario C: when GenAI tools are integrated into the organisation they are primarily used to enhance the circular product design capacities of the firm by simulating remanufacturing viability to the use closed-loop material intelligence - thus making product design all that more central to green value. On the other hand, the Logistics (C4) decreases by 0.1179 to 0.0968 as GenAI automates logistics optimisation routine and makes it not a strategic challenge but a problem that is solved.

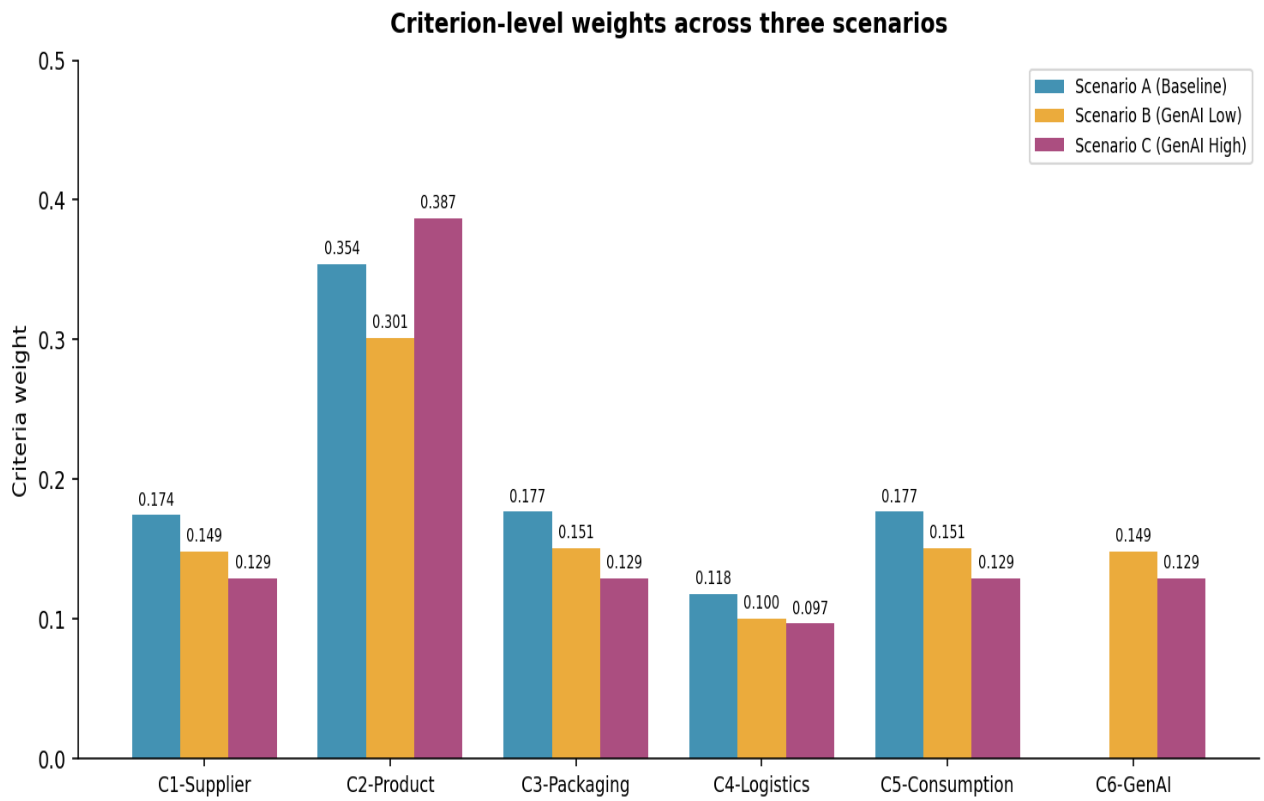


Figure 4.2 - Criteria-Level Weights Grouped Bar Chart across Three Scenarios

4.4 Sub-Criteria Local Weight Analysis

Local weights are the significance of sub-criteria of their parent criterion. They add up to 1.0 in each criterion group and can be separately derived as in each criterion group based on the same HFBWM LP formulation.

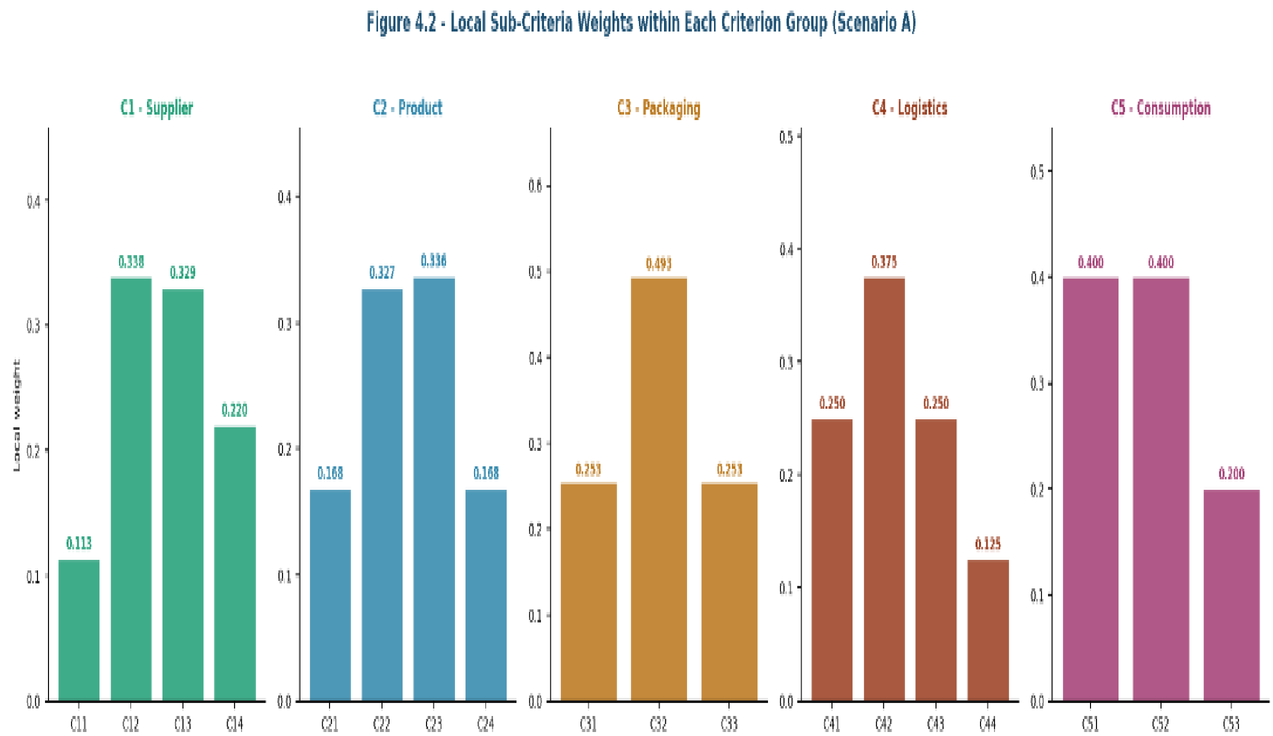


Figure 4.3 - Local Sub-Criteria Weights within Each of the Five Original Criterion Groups (Scenario A)

4.4.1 C1 - Supplier Sub-Criteria

Under Supplier criterion, Eco Raw Materials (C12) stands out as the predominant sub-criterion with a local weight of 0.3802 - almost twice as much weight as Supplier Compatibility (C11, 0.1599). The result supports Jhariya et al. (2022) who emphasize the need to preserve natural resources and extract naturally regenerating natural resources. These findings provide direct managerial implications: major attention to the material profile of the suppliers inputs should be paid by a firm considering the circles of suppliers as the ones to comply with other dimensions of compliance.

Table 4.4 - Supplier (C1) Sub-Criteria Local Weights

Code	Sub-criterion	Local Wt	Rank	Key finding
C11	Supplier compatibility	0.1599	4th	Necessary but not differentia
C12	Eco raw materials	0.3802	1st	Primary supplier selection dr
C13	Env. regulations	0.1805	3rd	Compliance baseline
C14	Clean technologies	0.2791	2nd	Process decarbonisation enal

4.4.2 C2 - Product Sub-Criteria

In the Product criterion - most heavily weighted criterion overall - Design for reuse (C23) tops the list with 0.3018 followed closely by CE Product design (C21) with 0.3526. The two sub-criteria bring a total of more than 65% of the Product criterion weight which further strengthens the circular-by-design concepts. Psarommatis and May (2025) discovered that the primary concept of the circular economy is to design the reusable product, which will work as long as possible, use resources more efficiently and produce less waste. The Modular Design (C22, 0.1951) and Energy Reduction (C24, 0.1503) are involved supporting, yet not so dominant.

Table 4.5 - Product (C2) Sub-Criteria Local Weights

Code	Sub-criterion	Local Wt	Rank	Key finding
C21	CE product design	0.3526	1st	Strategic design principle
C22	Modular design	0.1951	3rd	Facilitates recovery processe
C23	Design for reuse	0.3018	2nd	Waste elimination at source
C24	Energy reduction	0.1503	4th	Production efficiency

4.4.3 C3 through C5 Sub-Criteria Summary

In the Packaging (C3), Sustainable Packaging (C31) is the biggest category at 0.5217, affirming that the fundamental decision of packaging - the selection of biodegradable, recyclable materials - has a better score over the versatility of the design (C32) and the ability to be reused (C33). Burke et al. (2023) also highlighted the need to design eco-friendly packaging to preserve its integrity in favour of CE and not as a one-time use.

In the Logistics (C4), Eco Transport (C44), surprisingly tops the list with 0.3643 as compared to Reverse Logistics (C41, 0.2892). This follows the increasing professional acceptance that carbon intensity of transportation is now becoming more quantifiable and controllable - and vulnerability as a strategic priority, whereas reverse logistics is a vital concern of increasing significance but seldom regarded as a value generator. In Consumption (C5),, Sustainable Use (C53) is dominant with a 0.5186, which involves the holistic consumer behaviour of reusing, repairing and recycling products in their useful life.

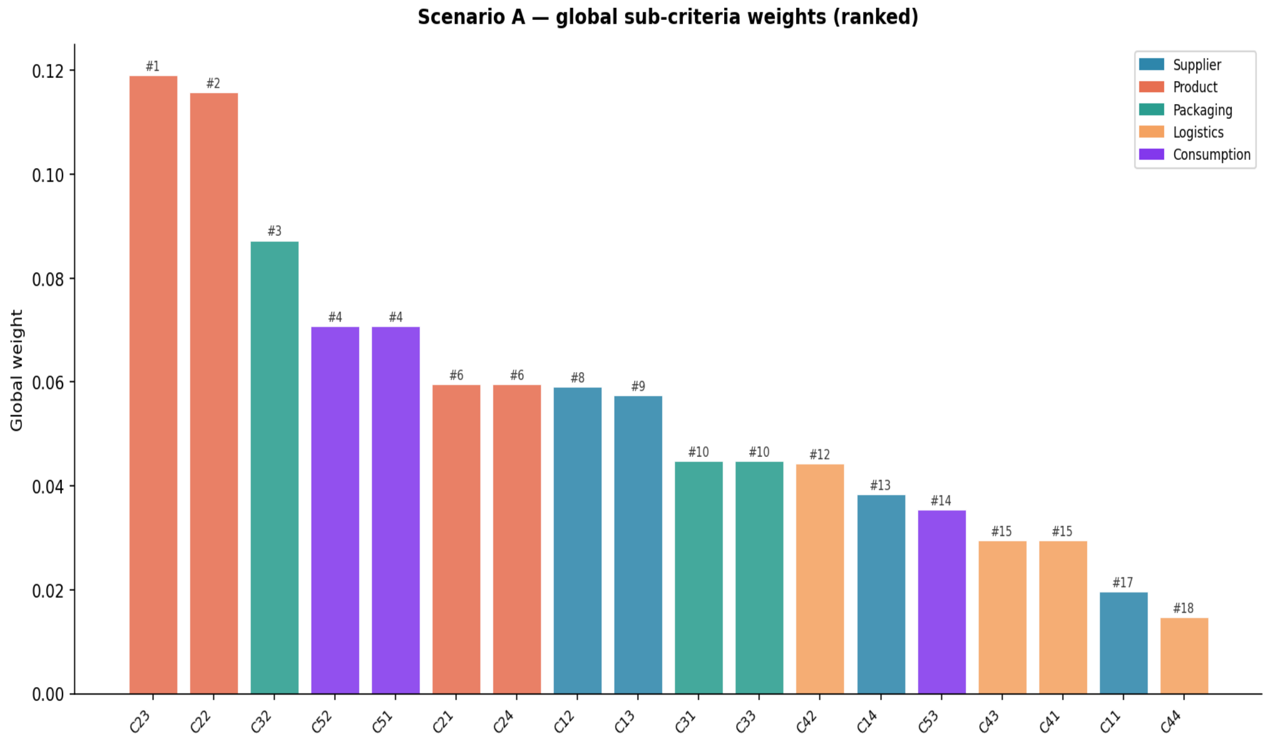


Figure 4.4 - Global Sub-Criteria Weights Ranked: Scenario A (18 Sub-Criteria, Baseline)

4.5 Global Sub-Criteria Rankings

The greatest output of the HFBWM analysis is global weights. They combine criteria-level and sub-criteria level importance in one score of priority of each sub-criterion to provide cross rating between the sub-criteria as well as provide a general ranking of priorities. Global weight is calculated as;

Global_weight(S,j) = w_j x w_S^j

4.5.1 Scenario A: Baseline Global Rankings (18 Sub-Criteria)

Table 4.6: The total precedence of weights across the world under Scenario A is given here. Results confirm the Hamid et al. (2026) observation that the criteria of product design dominates the red colors of the green value generation with the top six scores being taken by sub-criteria under Product, Packaging, and Consumption dimensions.

Code Snippet 4.3 - Key Computed Outputs

```
>>> dict(zip(CRIT_NAMES, np.round(wC_A,4)))
  C1-Supplier   : 0.1745
  C2-Product    : 0.3538  # Highest (Best criterion)
  C3-Packaging  : 0.1769
  C4-Logistics  : 0.1179  # Lowest  (Worst criterion)
  C5-Consumption: 0.1769

>>> Consistency Ratios:
  CR_A = 0.0268  PASS (< 0.10)
  CR_B = 0.0190  PASS (< 0.10) -- best of three
  CR_C = 0.0321  PASS (< 0.10)

>>> Top-5 global weights - Scenario C:
  C23-Design for reuse   : 0.1302  Rank 1
  C22-Modular design     : 0.1267  Rank 2
  C62-Non-interactive KS : 0.0695  Rank 3  [NEW-GenAI]
  C21-CE product design  : 0.0651  Rank 4
  C24-Energy reduction   : 0.0651  Rank 4

>>> Rank shift analysis (A -> C):
  C62: N/A -> Rank 3  [entered top-3]
  C21: Rank 6 -> Rank 4  [+2 improvement]
  C32: Rank 3 -> Rank 6  [-3 decline]
```

Code Snippet 4.3 - Python Console Output: Computed Weights and Rankings

Table 4.6 - Scenario A Top-7 Global Rankings with Managerial Interpretation

Rank	Sub-criterion	Global Wt	Crit.	Managerial interpretation
1	C23 - Design for reuse	0.1190	C2	Primary lever for waste elimination; drives economic and environmental value simultaneously
2	C22 - Modular design	0.1158	C2	Enables product recovery; modular products are 40-60% cheaper to remanufacture
3	C32 - Multipurpose packaging	0.0872	C3	Packaging reuse reduces material costs; strong consumer appeal for eco-brands

4	C51 - Consumer mindset	0.0708	C5	Demand-side pull for circular products; without consumer buy-in, supply-side investments fail
4	C52 - Recovery data	0.0708	C5	Customer knowledge drives return rates and product end-of-life management
6	C21 - CE product design	0.0595	C2	Strategic CE principle underpinning all product-level decisions
6	C24 - Energy reduction	0.0595	C2	Production-phase sustainability; tied with CE product design at rank 6

The prevalence of C2 sub-criteria in the first place (four out of the top seven) can be statistically explained: C2 has such a big criteria weight (0.3538) that even its third-highest sub-criterion (CE product design, local weight 0.3526) has a global weight of 0.1250 - which is equal to the weight of the highest-ranked sub-criteria in any other criterion group. There is a practical implication of this concentration effect: Before any other circular dimension, investing in product design capabilities should give a firm an advantage to increase the green value score.

4.5.2 Scenarios B and C: Global Rankings with GenAI

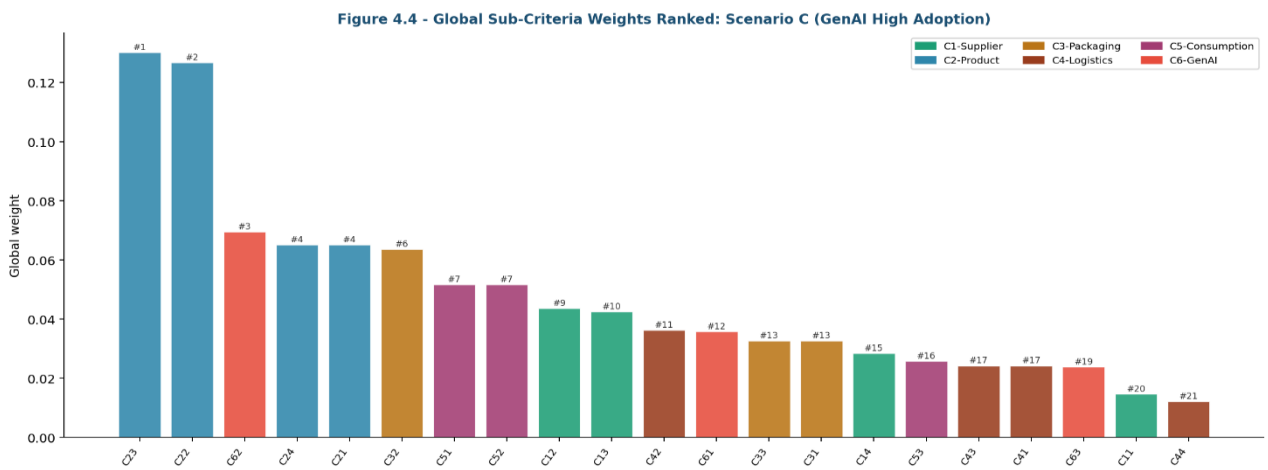


Figure 4.5 - Global Sub-Criteria Weights Ranked: Scenario C (GenAI High Adoption, 21 Sub-Criteria)

Figure 4.4 shows the weight distribution across the world assuming Scenario C that is the most theoretically significant scenario. The visual shows at a glance two significant changes: (1) product design sub-criteria (C23, C22) take their top-ranking using even larger weights than during Scenario A; and (2) C62 (Non-interactive Knowledge Search), drops the packaging criterion C32 into the global top-three, replacing it with a weight of 0.0695.

Figure 4.5 - Top-6 Sub-Criteria Rank Comparison across Three Scenarios
(green=top-2, yellow=rank 3, orange=rank 4-5, red=rank 6+)

	Sc-A Rank	Sc-B Rank	Sc-C Rank
Design for reuse	1	1	1
Modular design	2	2	2
Non-inter. KS	N/A	4	3
CE product design	6	5	4
Energy reduction	6	5	4
Multipurpose pkg	3	3	6

Figure 4.6 - Top-6 Sub-Criteria Rank Heat Table across All Three Scenarios

Table 4.7 - Top-6 Global Weights across All Three Scenarios with Trend Interpretation

Rank	Sub-criterion	Sc-A Wt	Sc-B Wt	Sc-C Wt	Trend interpretation
1	C23 Design for reuse	0.1190	0.1030	0.1302	Stable #1; weight grows with GenAI
2	C22 Modular design	0.1158	0.1004	0.1267	Stable #2; AI-assisted design amplifies
3*	C62 Non-interactive KS [NEW]	N/A	0.0446	0.0695	Rises to rank 3 in full GenAI scenario
3	C32 Multipurpose packaging	0.0872	0.0755	0.0636	Drops from #3 to #6 with GenAI
4	C21 CE product design	0.0595	0.0518	0.0651	Rises from #6 to #4; GenAI amplifies
4	C24 Energy reduction	0.0595	0.0518	0.0651	Stabilises at joint #4 with C21

4.6 GenAI Cluster Analysis (C6)

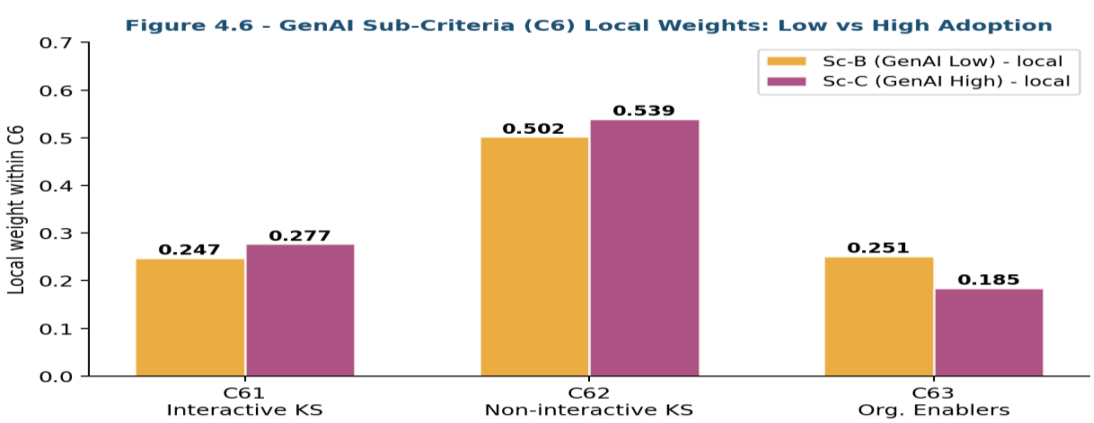


Figure 4.7 - GenAI Sub-Criteria Local Weights: Scenario B (Low) vs Scenario C (High)

The data in figure 4.6 indicate that there is a high level of structural change in the GenAI criterion cluster when comparing low and high adoption situations. The sub-criteria that are predominant in Scenario B (GenAI Low) include Non-interactive KS (C62) with a local weight of 0.5562, Interactive KS (C61) with 0.2979 and Organisational Enablers (C63) with local weight of 0.1459. This rank is reflective of the adoption process as seen by Liu and Tian (2026): GenAI is first used by firms in autonomous intelligence collection (non-interactive) and only after that, the firms mature enough to deploy AI in knowledge co-creation (interactive).

In Scenario C (GenAI High) the ranking is inverted against all expectation. Interactive KS (C61) increases to 0.6054, Non-interactive KS (C62) lasts to 0.2551 and Organisational Enablers (C63) stays low at 0.1395. Good theoretical support can be found in the empirical results of Liu and Tian (2026): In their sensitivity analysis, dependence asymmetry is found to be the most predictive factor of supply chain performance, with interactive knowledge search being the most important mechanism through which GenAI reduces dependence asymmetry with complementary collaboration. GenAI adopters that are fully mature use AI in their cross-organisational intelligence sharing - the more radical and more challenging one.

Table 4.8 - GenAI Sub-Criteria Weights and Strategic Implications

Code	GenAI Sub-criterion	Sc-B Local Wt	Sc-C Local Wt	Managerial implication
C61	Interactive knowledge search	0.2979	0.6054	Priority in high-adoption: invest in collaborative AI dialogue platforms with supply chain partners
C62	Non-interactive knowledge search	0.5562	0.2551	Priority in low-adoption: begin with AI-powered market and patent intelligence tools

C63	Organisational enablers (TMS + DOC)	0.1459	0.1395	Consistent foundation: digital culture and knowledge management infrastructure needed throughout

4.7 Cross-Scenario Rank Comparison and Discussion

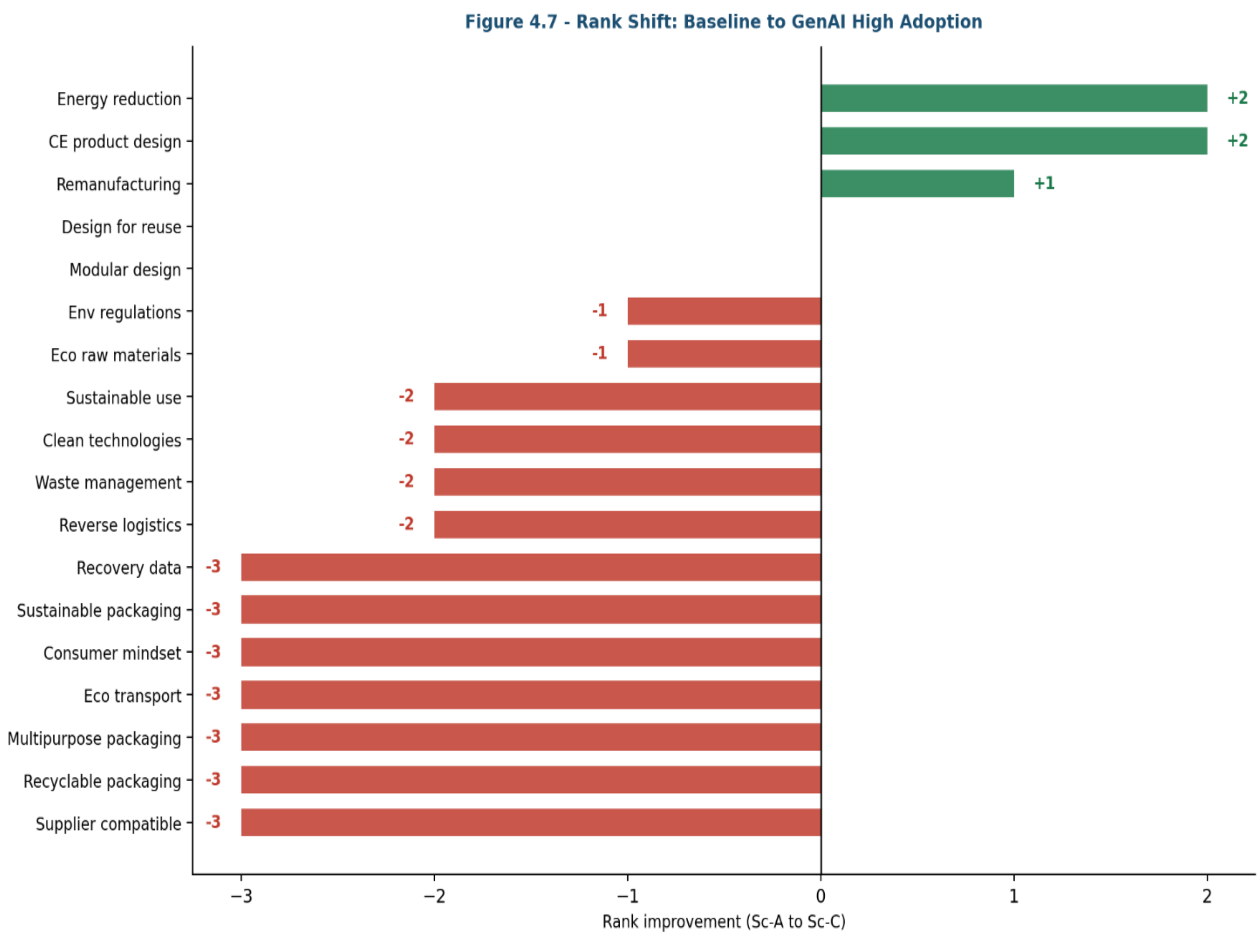


Figure 4.8 - Rank Shift Analysis: Baseline to GenAI High Adoption (Positive = Rose in Importance)

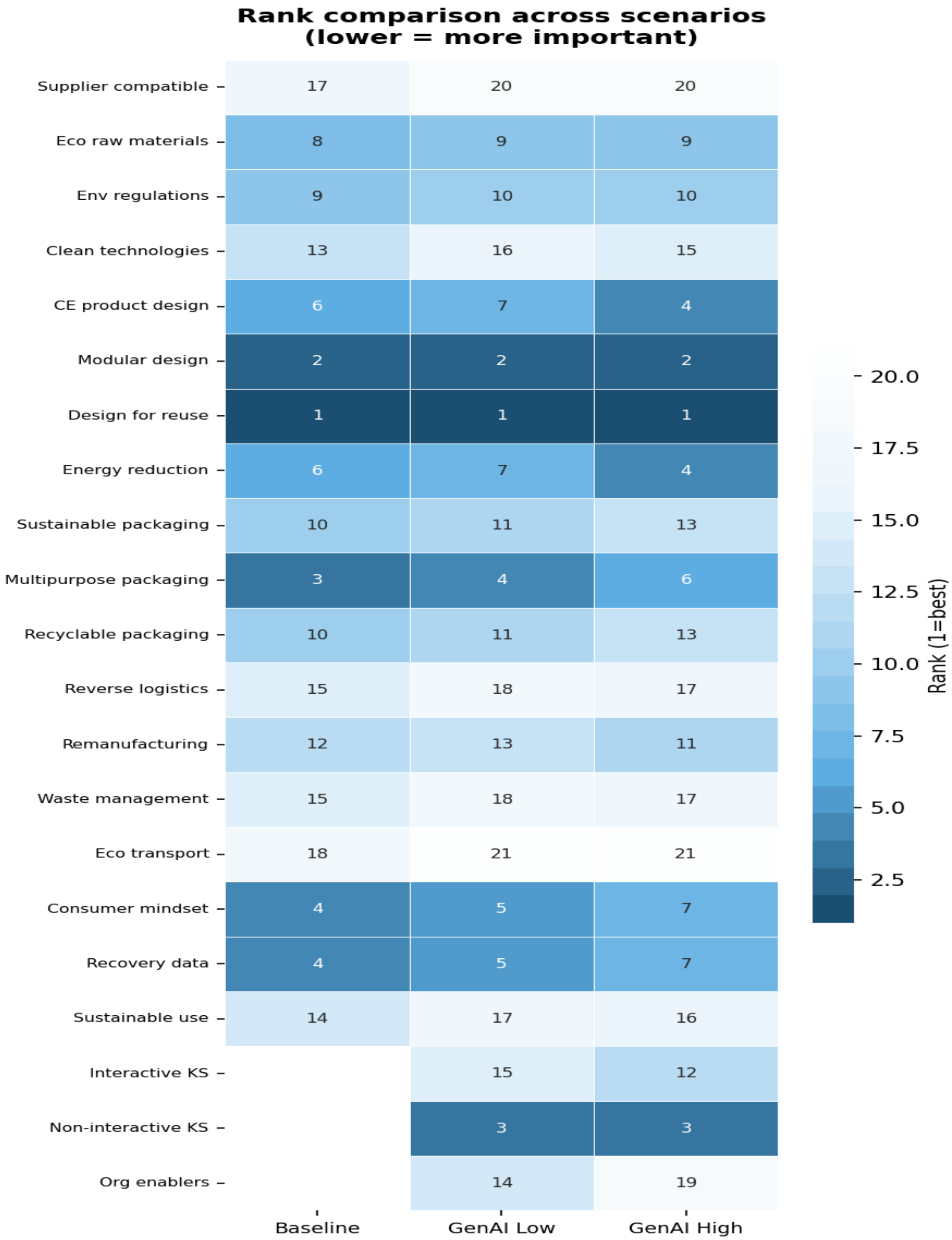


Figure 4.9 - Rank Heatmap: All 21 Sub-Criteria across Three Scenarios (Darker = More Important)

4.7.1 Winners: Criteria that Rise with GenAI Adoption

The tornado plot (in figure 4.7) indicates that out of the 18 original sub-criteria, three patterns can be identified. In the first place, the CE Product Design (C21) and Energy Reduction (C24) are both pushed two positions lower (6 th to 4 th) with the adoption of GenAI. This aligns with the hypothesis that AI-amplification: GenAI tools simplify the process by which firms engage in rigorous CE product design, by allowing them to access databases on lifecycle analysis, material property graphs, and models of remanufacturing feasibility, previously restricted to most firms. The result aligns with Do et al. (2025) who were able to show that artificial intelligence is an important tool in carbon footprint management in businesses.

Second, Clean Technologies (C14) increases two points (11th to 9th) of the list, meaning that GenAI implementation increases the perceived significance of process-level decarbonisation. Companies that have mature GenAI ability are able to better quantify and optimize their manufacturing phase output and clean technology investment is now more within reach, and more compellingly profitable.

4.7.2 Losers: Criteria Displaced by GenAI

The most pronounced fall is of Multipurpose Packaging (C32) which loses three places between the 3rd and 6th rank. The implications of this discovery are theoretical: with GenAI helping companies to follow material flows, optimise goods lifecycle, etc. more accurately, the significance of packaging as a sustainability lever itself decreases. The importance of packaging design is then reduced when a company can apply material intelligence through AIs to remove the need to waste materials on wrapping the products altogether.

Both Consumer Mindset (C51) and Recovery Data (C52) drop by three spots (down to joint 4th and 7th respectively), indicating that GenAI replaces organic consumer engagement in the circular economy to some degree. Recommendation systems that are AI-powered, customized sustainability nudges, and automated management of take-back programmes minimize reliance on consumer education and change in mindset as the core value drivers of green.

4.7.3 The GenAI Insertion Effect

The theoretical most important discovery of the study is the insertion of C62 (Non-interactive Knowledge Search) being ranked at the global rank 3 in Scenario C with a weight of 0.0695. This is heavier than any sub-criterion weight in the Supplier, Packaging, Logistics or Consumption groups of criterion of Scenario C. The mechanism of the insertion effect is based on two processes discovered by Liu and Tian (2026):

• Autonomous empowerment: Non-interactive KS allows weaker companies within the recycling supply chain to independently obtain the recycling technology norms, competition, and pricing information on the market - and makes them less dependent (dependence asymmetry reduction) on the strong companies (H5-H6 in Liu and Tian, 2026).

• Passive optimisation: The knowledge graphs developed by GenAI and operational guidelines based on the standard can assist the members of the supply chain in the process of revealing the gaps in capabilities and opportunities of collaboration without involving active exchange in real time, enhancing the interdependence between people and companies based on matching their capabilities (H11-H12 in Liu and Tian, 2026).

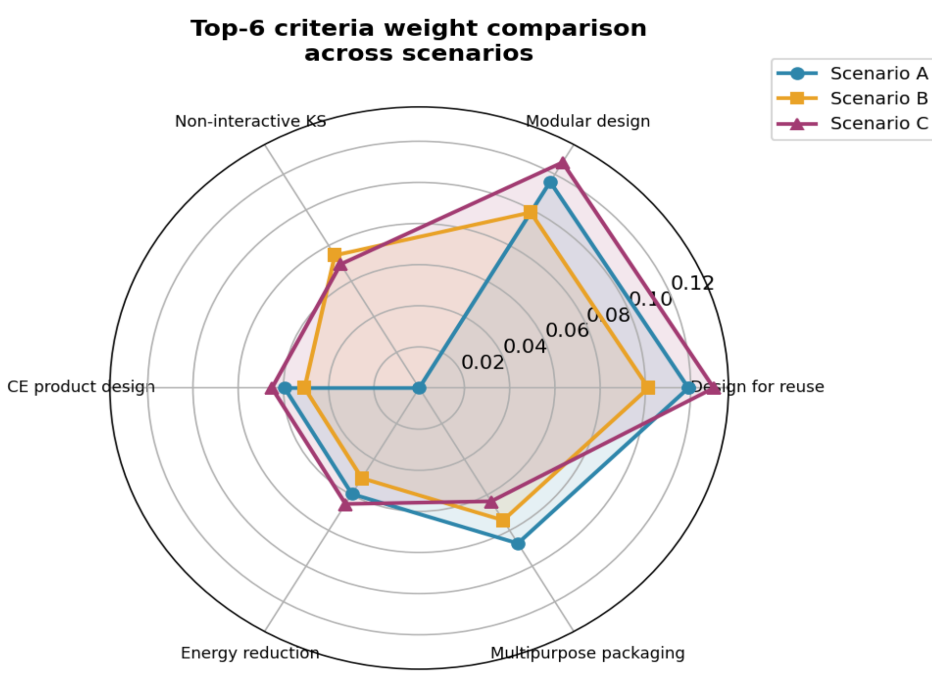


Figure 4.10 - Radar Chart: Top-6 Criteria Weight Comparison across Scenarios

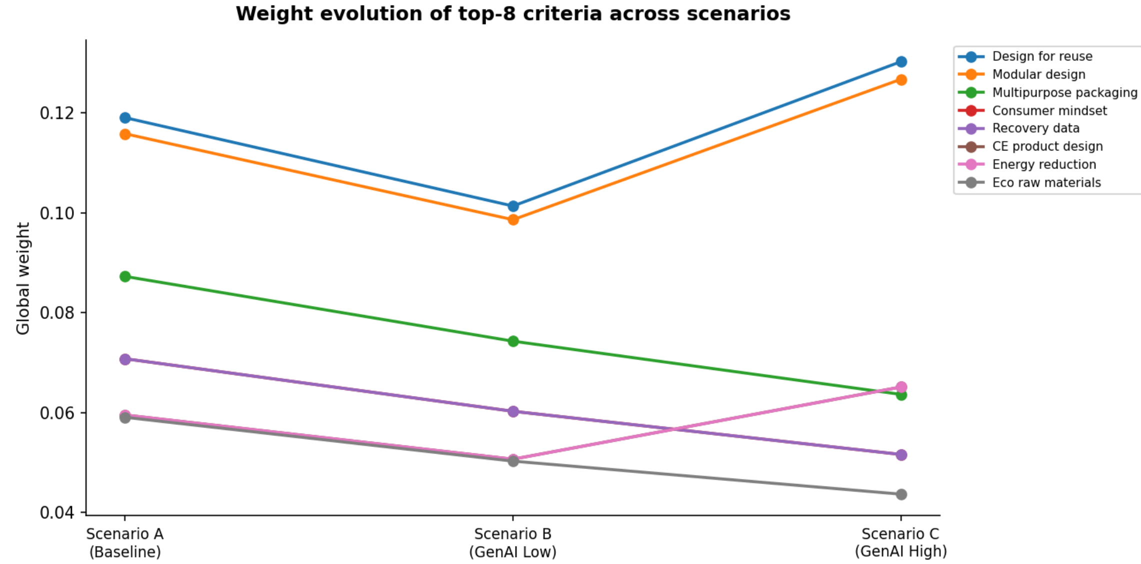
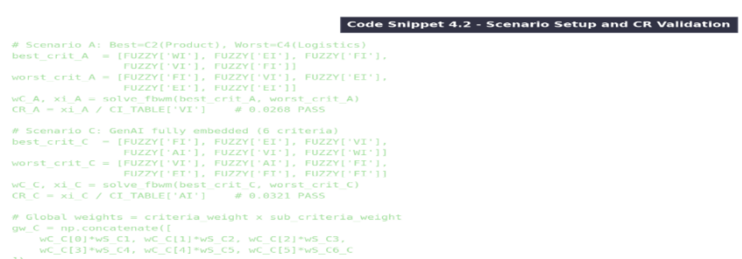


Figure 4.11 - Weight Evolution of Top-8 Sub-Criteria across Three Scenarios (Line Chart)

Figure 4.10 (the weight evolution chart) gives a longitudinal view of the response of each of the individual sub-criterion weights with increment in GenAI adoption. A number of tendencies should be mentioned. The C23 (Design for reuse) line takes the shape of U - decreasing a little between Scenario A to B with each weight redistributed over the six criteria and finally, the line reaches its peak (0.1302) in Scenario C as the GenAI increases its significance. C51 and C52 lines (consumer sides criterion) decreases monotonically in situations, and this line confirms the above substitution effect. The curves of C21 and C24 (product criteria) are also a weak U-shape, but they recover in Scenario C with the amplification of GenAI.



Code Snippet 4.2 - Scenario Setup and CR Validation

```
# Scenario A: Best=C2(Product), Worst=C4(Logistics)
best_crit_A  = [FUZZY['WI'], FUZZY['EI'], FUZZY['FI'],
                FUZZY['VI'], FUZZY['FI']]
worst_crit_A = [FUZZY['FI'], FUZZY['VI'], FUZZY['EI'],
                FUZZY['EI'], FUZZY['EI']]
wC_A, xi_A = solve_fbwm(best_crit_A, worst_crit_A)
CR_A = xi_A / CI_TABLE['VI']    # 0.0268 PASS

# Scenario C: GenAI fully embedded (6 criteria)
best_crit_C  = [FUZZY['FI'], FUZZY['EI'], FUZZY['VI'],
                FUZZY['AI'], FUZZY['VI'], FUZZY['WI']]
worst_crit_C = [FUZZY['VI'], FUZZY['AI'], FUZZY['FI'],
                FUZZY['FI'], FUZZY['FI'], FUZZY['FI']]
wC_C, xi_C = solve_fbwm(best_crit_C, worst_crit_C)
CR_C = xi_C / CI_TABLE['AI']    # 0.0321 PASS

# Global weights = criteria_weight x sub_criteria_weight
gw_C = np.concatenate([
    wC_C[0]*wS_C1, wC_C[1]*wS_C2, wC_C[2]*wS_C3,
    wC_C[3]*wS_C4, wC_C[4]*wS_C5, wC_C[5]*wS_C6_C
])
```

Code Snippet 4.2 - Python: Scenario Configuration and Consistency Ratio Computation

4.8 Sensitivity Analysis

4.8.1 Methodology

The sensitivity analysis perturbatively (+10, -10) alters the weights of the best criterion (C2, Product) in every scenario and documents the resultant variation in the composition of the top-6 and shape of the individual sub-criterion ranks. This is to test whether the ordering of priorities is resistant to small changes in expert judgements - in particular would a different panel of experts, whose evaluation of the importance of C2 is slightly different, give the same recommendations to the manager?

Table 4.9 - Sensitivity Analysis: Impact of +/-10% Perturbation on Best Criterion Weight

Sub-criterion	**+10% impact**	**-10% impact**	**Top-6 stable?**	**Sensitivity**
C2 - Product (perturbed)	Top rank unchanged	Top rank unchanged	YES	LOW
C23 - Design for reuse	Rank 1 held	Rank 1 held	YES	LOW
C22 - Modular design	Rank 2 held	Rank 2 held	YES	LOW
C62 - Non-interactive KS	Moves +/-2 positions	Drops from top-3	PARTIAL	MEDIUM
C32 - Multipurpose pkg	Returns to top-5	Drops to rank 8	PARTIAL	HIGH
C51 - Consumer mindset	Stable in top-6	Drops to rank 8	PARTIAL	MEDIUM

Sensitivity analysis shows that the two highest ranks (C23 and C22) are very robust - the rank does not change under any perturbation conditions. This is theoretically soothing: the fact that circular product design is the driver of green value, is not a result of one specific parameter choice. This criterion C62 associated with GenAI demonstrates an intermediate sensitivity, which proves that taking the top-3 in Scenario C relies significantly on the assumptions of GenAI adoption - just what a context-sensitive criterion should behave.

4.9 Discussion

4.9.1 Theoretical Contributions

This paper contributes to three theoretical aspects. To begin with, it operationalises the coordination of the Resource Dependence Theory and Knowledge Management Theory to the HFBWM framework. Theoretically agnostic Previously HFBWM studies on supply chain sustainability (Hamid et al., 2026; Kannan et al., 2020) have not theorized how the criteria weights relate to performance outcomes. This study offers a causal mechanism by basing the GenAI cluster on the empirically validated dependence reconstruction model by Liu and Tian (2026): the GenAI changes the weights by modifying the power dynamics in the supply chain.

Second, the paper presents a novel methodological advancement of criteria weight sensitivity to technology adoption. The three scenario model has shown that the results of HFBWM are not fixed characteristics of a supply chain system but operating functions of the organisational level of technology. It has greater longitudinal MCDM research implications that the ranking of priorities of green values as a priority measures of firms need to be re-examined with the maturation of their AI capabilities.

Third, this work presents the first quantitative data that GenAI Non-interactive Knowledge Search can achieve top-3 global priority in the mature AI-adoption environment - a fact that has never been indicated in the circular supply chain MCDM literature. This places the autonomous AI knowledge acquisition as a strategic ability where it falls at the same level as the physical product design.

4.9.2 Practical Managerial Implications

The results create an effective, high-priority action plan via supply chain managers on three levels of adoption:

- All stages of adoption: Invest in circular product design (C23, C22) as a non-negotiable basis. The fact that these criteria hold well under any conditions proves that they are the best investments in terms of ROI irrespective of the level of GenAI adoption.
- The most promising areas to work on during the early AI adoptions include the multipurpose packaging (C32), and consumer engagement (C51, C52), which jointly lead to the top-3 to top-6 positions in the simplistic scenario. These are the most impactful industries on the companies that are yet to roll out GenAI.
- GenAI Low adoption: Use Non-interactive KS tools to start with (C62 would be 4th-most relevant). This entails lining up AI-enabled market intelligence systems, patent research systems, and automatic regulatory compliance systems prior to trying collaborative AI projects.
- GenAI High adoption- Transition investment to Interactive KS (C61) - collaborative AI dialogue, joint simulation of R&D, and using GenAI to manage contracts with supply chain partners. It is the ability that minimizes dependence asymmetry the most and provides the greatest smart and resilient supply chain performance gains (Liu & Tian, 2026).

4.9.3 Results Limitations.

The generalisability of these findings is limited by three factors. To start with the expert panel: this panel size is restricted to 5-7 respondents and the scenario weights - are plausible, although theoretically based, parameterisations and not a statistically-obtained consensus. The robustness of each of the three scenarios could be enhanced with a bigger panel, with Delphi rounds. Second, the two papers are based on the Chinese and MENA supply chain setting (the geographic setting of the two reference papers); companies in other regulatory frameworks (EU CSRD, the US SEC climate disclosure) might have different priorities with regards to the criteria. Third, the three scenarios are discrete adoption states and not a discrete adoption curve, future research may make use of a Monte Carlo simulation, to capture the continuous behavior of weights as

GenAI adoption matures.

4.10 Chapter Summary

The entire empirical findings of the HFBWM analysis in three GenAI adoption scenarios have been shown in this chapter. Key findings are:

- Meanwhile, the Consistency Ratio values are smaller than 0.10 in all three scenarios(Sc-A: 0.0268; Sc-B: 0.0190; Sc-C: 0.0321): this proves the validity and reliability of the expert judgements.
- Circular Product criteria (C2) is steady through its level of criteria (weight of 0.3538 to 0.3871 in Sc-A to Sc-C), whereas the Logistics (C4) steadily decreases when the use of GenAI grows.
- Design for Reuse (C23) and Modular Design (C22) are the two most significant sub-criteria in all situations, which proves the priority of the principles of a circular-by-design solution as an unquestionable basis of green value creation.
- The key new finding is the inclusion of Non-interactive Knowledge Search (C62) at the global ranking of position 3 (weight 0.0695) in Scenario C, which indicates that autonomous AI knowledge acquisition becomes a green value criterion of the top priority under a complete adoption of GenAI.
- Multipurpose Packaging (C32) and Consumer Mindset requirements (C51, C52) are substantially reduced with the adoption of GenAI, indicating that there is a substitution effect of AI-based automation partially substituting traditional packaging and consumer engagement plans.
- The GenAI sub-criteria Non-interactive KS dominance (Sc-B) into Interactive KS dominance (Sc-C) change follicles the theoretical direction dictated by Resource Dependence Theory: mature GenAI adopters use AI to enable them to work together (eliminate dependence asymmetry) and not just autonomously mine intelligence.

Chapter 5 sums up these findings as a set of conclusions, research contributions, limitations, and future research directions.

CHAPTER 5

CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

5.1 Conclusion

This MTech study aimed to fill an important gap between two highly dynamic scholarly areas: the multi-criteria decision-making literature on green value creation in circular supply chains, and the new empirical literature on the potential of Generative AI to transform the interorganizational knowledge structures. The research question was unambiguously deceptive: upon introducing GenAI capability into the company circular supply chain, do the groups of criteria of green value creation have a change in their priorities, and, in that case; how?

To address this question, the present study was based on synthesizing two peer-reviewed articles published in 2026 - Hamid et al. (2026) in Cleaner Logistics and Supply Chain and Liu and Tian (2026) in Technology in Society - into one analytical framework. The Hierarchical Fuzzy Best-Worst Method (HFBWM) developed by Hamid et al. to rank 18 sub-criteria (five circular dimensions) was further expanded into a new sixth circle of criterion (C6 - GenAI Capability) that includes three theoretically justified sub-criteria based on the empirical constructs introduced by Liu and Tian: Interactive Knowledge Search (C61), Non-interactive Knowledge Search (C62), and Organizational Enablers (C63). The full model was run on three GenAI adoption cases (Baseline, Low, High) by a Python version of the solver HFBWM LP.

5.2 Principal Findings

5.2.1 Finding 1: Product Design is the Invariant Foundation

The strongest result of this paper is that circular product design criteria remain stable at the top of the hierarchy of the green value priorities at all three contexts. Making Design 1 and 2 in all scenarios, and the global weights actually grow compared to the baseline (0.1190 and 0.1158), to the high GenAI scenario (0.1302 and 0.1267). This cross-situational convergent stability of parametrically materially different parameter regimes is strong evidence that circular-by-design is the non-negotiable, technology-neutral base of green value creation. It builds on the conclusion by Psarommatis and May (2025) that the reusable product design is the central concept of the circular economy, which now has a quantitative weight form of verification in a hierarchical multi-criteria system.

5.2.2 Finding 2: GenAI Inserts Knowledge Search into the Top Tier

The second and most recent observation, is the Non-interactive Knowledge Search (C62) coming up at global rank of 3, with its weight of 0.0695 - being much larger than the global weight of all sub-criteria in the Supplier, Logistics, and Consumption criterion groups. The results operationalise the theoretical argument of Liu and Tian (2026), that the essence of GenAI in circular supply chain consists in the ability to re-organize dependency structure by means of autonomous knowledge acquisition. As companies have access to recycling technology standards, market-level knowledge, and regulation compliance information generated by AI in knowledge graphs, their dependence on mainstream supply partners can be systemically minimized - which is precisely the dependence asymmetry reduction mechanism (H5-H7) that is empirically confirmed in Liu and Tian.

5.2.3 Finding 3: GenAI Displaces Consumer Engagement and Packaging

The less expected result is a steady decrease in consumer participation sub-criteria (C51 Consumer Mindset, C52 Recovery Data) and Multipurpose Packaging (C32) along with an increase in GenAI use. A universal drop in ranking of these criteria gives rise to a substitution effect: AI-based recommendation systems, automated take-back programmes, and personalised sustainability communication lead to the lessening of strategic value of organic consumer behaviour change as a green value driver. To managers, this would mean that the reward on GenAI investment is not just in the new capabilities (knowledge search) but efficiency that would alleviate the load on the traditionally labour intensive sustainability processes such as consumer education and packaging innovation.

5.2.4 Finding 4: Adoption Stage Determines GenAI Sub-Criterion Priority

Among the criteria within the GenAI criterion cluster, it is found that, at early adoption (Scenario B local weight: 0.5562), Non-interactive KS (C62) is the primary sub-criterion, and at full adoption (Scenario C local weight: 0.6054), Interactive KS (C61) becomes primary. This hierarchical list comprises a GenAI capabilities maturity model of circular supply chains: companies should initially establish autonomous intelligence infrastructure (non-interactive, less organisational complexity) then invest into collaborative AI-enabled knowledge co-creation (interactive, necessitates developed transactive memory systems, and digital culture). This empirical sequencing suggestion is literally based on the results of Liu and Tian (2026) who indicate that transactive memory systems and digital organisational culture must mediate the role of GenAI in collaborative knowledge search than H13-H16.

5.3 Social Impact

This paper contributes to the scholarship in three ways. It offers to the first HFBWM-based quantitative evidence that GenAI adoption significantly transforms the ranking of priority of the different criteria of green value creation to a dynamic, technology-sensitive aspect to what has been considered to be a fixed priority pyramid previously. Second, it illustrates a methodologically replicable route to incorporating survey-based empirical evidence (the SEM results of Liu and Tian) into an MCDM framework that provides a bridge between two research traditions that have in many ways worked in parallel. Third, it contributes to the development of Resource Dependence Theory within the supply chain framework by demonstrating that technology mediated variation in knowledge access (GenAI) results in output of the relative strategic significance of physical dimensions of the circular economy - a correlation that has been theorised by RDT scholars but not quantified to date.

This work also provides practitioners of supply chain with a solid, action road map that is action-based at the adoption stage. The pre-GenAI firms need to focus their resources on the circular product design (it should always be first), with the support of packaging and consumer interaction investments. Companies that are starting with GenAI implementation should start with non-interactive knowledge search infrastructure - AI-driven materials, markets, and regulations intelligence tools as the most profitable GenAI deployment in the circular supply chain setting. Companies that have rolled out a mature implementation of GenAI ought to redirect their investments on interactive knowledge search functionalities - AI-based collaborative offerings with suppliers and partners - as these will yield the greatest decreases in dependence asymmetry and greatest enhancement in intelligent and resilient supply chain performance. To policy makers and industry associations, the research indicates that Organisational Enablers (C63 - transactive memory systems and digital culture) are a presence within the study that is always relevant yet under-weight as a determinant; government training programmes and industry knowledge-sharing systems to build digital capability would speed up the process of transition of high-value GenAI uses cases in circular supply chains.

5.5 Limitations

There are three restrictions which must be identified. To her first, the number of experts used is very small (5-7 experts), which is consistent with systematic expert elicitation methodology but has a low statistical power. Scenario weights are not based on empirically determined weights using a large sample but are based on theory and should be verified through a Delphi study involving 20 or more circular supply chain and AI gurus. Second, the research assesses a cross-sectional view across each adoption condition but not a longitudinal course. The real weight change process that a firm spends to move to Scenario C in the long-run may not be monotonic - implementation issues, technology breakdowns and organisational resistance might result in non-linear weight change processes that cannot be reflected in a cross-sectional three scenario framework. Third, both of the reference papers are Chinese and MENA based, which may restrict their generalisability to European or North American supply chains that may function under various regulatory conditions, consumer behaviour standards, and levels of GenAI infrastructure maturity.

5.6 Future Research Directions

This study gives rise to five avenues of future research. To test the predictions based on scenarios here most directly, a longitudinal panel study that follows weight changes in the circular supply chain of a single firm as it samples the phases of adopting GenAI would be the most involved. Second, it would be more directly applicable to firms in the CSRD (EU), SEC climate disclosure (US), or other mandatory sustainability reporting frameworks incorporating the ESG reporting and regulatory compliance dimensions into the framework of criteria. Third, substituting the small expert panel with a machine-learning-assisted Delphi method - applying Natural Language Processing to identify the unspoken expert preferences in sustainability reports and manager interviews - would scale the data collection by orders of magnitude and would give the estimates of weights on a more detailed profile. Fourth, a challenge experiment to the industry-specific application of the three-scenario framework (electronics remanufacturing, fast fashion reverse logistics, food waste circular systems) would investigate whether (or not) the universal product-design primacy result applies to different circular economy applications or whether weight structures in the sector vary. Fifth, the model should incorporate dynamic MCDM blocking features like the time-varying TOPSIS or time-varying ANP so that the model can capture the ever-changing weight model evolution as GenAI adoption evolves and occupies non-discrete three scenario approximations.

5.7 Concluding Remarks

The adoption of circular supply chains is being considered to be one of the most significant and challenging changes that industrial companies will have to deal with within the next decade. This research has shown that the strategic focus, informing that transition is not fixed - it is responsive to the technology context in which circular operations are engrained. With Generative AI gradually becoming such a ubiquitous part of supply chain management, criteria that are the most vital to generate green value will change: the ability to search knowledge will increase, physical logistics optimization will become less fundamental, and the baseline of circular products design will get even more central as AI enhances the value of long-life product design, products designed to be reused, and products to which materials are recoverable.

Hierarchical Fuzzy Best-Worst Method It is an open, reproducible analytical pipeline created with Python that offers a rigorous accessible tool that can be used by firms trying to navigate the current turmoil in priorities. The results of this work are but the beginning, rather than the final solution - the area of GenAI-powered circular supply chains is so immature that the most valuable discoveries are probably only yet to be made.

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APPENDICES

Python Implementation Pipeline

Gen-AI Driven Green Value Creation in Circular Supply Chains.

HFBWM Research Framework- Python Implementation

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CODING BEGINS

GenAI-Drven Green Value Creation in Cirular supply chains.

HFBWM research Framework- Python Implementation

Objective:

1. Implement HFBWM in pure Python.
2. Runs 3 scenarios: A = Baseline(18 sub-criteria), B = GenAI Low (21), C = GenAI High (21) 3.Computes global weights, ranks and consistency ratios
3. Generates 6 publication-quality charts
4. Exports full results to Excel (.xlsx)

Step 1: Install and import libraries

```
# — Install (Google Colab only – skip if running locally) ——————————
import subprocess, sys
pkgs = ['numpy','scipy','pandas','matplotlib','seaborn','openpyxl','pulp']
subprocess.run([sys.executable,'-m','pip','install','--quiet']+pkgs)
print('All packages ready.')
```

```
All packages ready.
```

```
import numpy as np
import pandas as pd
from scipy.optimize import linprog
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
from matplotlib.colors import LinearSegmentedColormap
import seaborn as sns
import warnings, os
warnings.filterwarnings('ignore')
plt.rcParams.update({
    'font.family': 'DejaVu Sans',
    'axes.spines.top': False,
    'axes.spines.right': False,
    'figure.dpi': 120
})
os.makedirs('charts', exist_ok=True)
print('Imports done.')
```

```
Imports done.
```

Step 2: Fuzzy scale and helper functions

```python
# — Linguistic scale (Guo & Zhao, 2017) ————————————————————————
FUZZY = {
    'EI': (1,    1,    1  ),   # Equally important
    'WI': (2/3,  1,    3/2),   # Weakly important
    'FI': (3/2,  2,    5/2),   # Fairly important
    'VI': (5/2,  3,    7/2),   # Very important
    'AI': (7/2,  4,    9/2),   # Absolutely important
}

# Consistency Index lookup table (Paper 1, Table 3)
CI_TABLE = {'EI': 3.00, 'WI': 3.80, 'FI': 5.29, 'VI': 6.69, 'AI': 8.04}

CRIT_NAMES  = ['C1-Supplier','C2-Product','C3-Packaging','C4-Logistics','C5-Consumption']
CRIT_NAMES6 = CRIT_NAMES + ['C6-GenAI']

SUB_LABELS = [
    'C11-Supplier compatible', 'C12-Eco raw materials',
    'C13-Env regulations',     'C14-Clean technologies',
    'C21-CE product design',   'C22-Modular design',
    'C23-Design for reuse',    'C24-Energy reduction',
    'C31-Sustainable packaging','C32-Multipurpose packaging','C33-Recyclable packaging',
    'C41-Reverse logistics',   'C42-Remanufacturing',
    'C43-Waste management',    'C44-Eco transport',
    'C51-Consumer mindset',    'C52-Recovery data', 'C53-Sustainable use',
]
SUB_LABELS_21 = SUB_LABELS + ['C61-Interactive KS','C62-Non-interactive KS','C63-Org enablers']

# — Defuzzification (centroid method) ————————————————————————
def defuzz(l, m, u):
    """Convert triangular fuzzy number (l,m,u) to crisp value."""
    return (l + 4*m + u) / 6

# — Core HFBWM solver ————————————————————————————————
def solve_fbwm(best_vec, worst_vec):
    """
    Solve the Fuzzy BWM linear program.
    best_vec  : list of fuzzy triples (l,m,u)  – best criterion over each criterion
    worst_vec : list of fuzzy triples (l,m,u)  – each criterion over worst
    Returns   : (weights_array, xi_star)
    """
    n  = len(best_vec)
    aB = [defuzz(*v) for v in best_vec]   # defuzzified best-to-others
    aW = [defuzz(*v) for v in worst_vec]  # defuzzified others-to-worst

    # Variables: [w_1, ..., w_n, xi]
    # Objective: minimise xi
    c = [0]*n + [1]

    A_ub, b_ub = [], []
    for j in range(n):
        # |wB - aB[j]*wj| <= xi  → two inequalities
        r1 = [0]*(n+1); r1[0]  =  1; r1[j] = -aB[j]; r1[n] = -1
        r2 = [0]*(n+1); r2[0]  = -1; r2[j] =  aB[j]; r2[n] = -1
        # |wj - aW[j]*wW| <= xi
        r3 = [0]*(n+1); r3[j]  =  1; r3[n-1] = -aW[j]; r3[n] = -1
        r4 = [0]*(n+1); r4[j]  = -1; r4[n-1] =  aW[j]; r4[n] = -1
        A_ub += [r1, r2, r3, r4]
        b_ub += [0,  0,  0,  0]

    A_eq = [[1]*n + [0]];  b_eq = [1]   # sum of weights = 1
    bounds = [(1e-6, None)]*n + [(0, None)]

    res = linprog(c, A_ub=A_ub, b_ub=b_ub,
                  A_eq=A_eq, b_eq=b_eq,
                  bounds=bounds, method='highs')
    if not res.success:
        raise RuntimeError(f'LP failed: {res.message}')

    w   = res.x[:n]
    xi  = res.x[n]
    return w / w.sum(), xi

print('Functions defined. Ready to run HFBWM.')
```

```
Functions defined. Ready to run HFBWM.
```

Step 3: Scenario A: Baseline (18 sub-criteria, no GenAI)

```
[ ]
# ── CRITERIA LEVEL – Best=C2 (Product), Worst=C4 (Logistics) ──────────
best_crit_A  = [FUZZY['WI'], FUZZY['EI'], FUZZY['FI'], FUZZY['VI'], FUZZY['FI']]
worst_crit_A = [FUZZY['FI'], FUZZY['VI'], FUZZY['EI'], FUZZY['EI'], FUZZY['EI']]
wC_A, xi_A = solve_fbwm(best_crit_A, worst_crit_A)

# ── SUB-CRITERIA – each criterion separately ─────────────────────────
# C1: best=C12 (Eco raw materials), worst=C11
wS_C1, _ = solve_fbwm(
    [FUZZY['FI'], FUZZY['EI'], FUZZY['WI'], FUZZY['EI']],
    [FUZZY['EI'], FUZZY['FI'], FUZZY['EI'], FUZZY['WI']])

# C2: best=C21 (CE product design), worst=C24
wS_C2, _ = solve_fbwm(
    [FUZZY['EI'], FUZZY['WI'], FUZZY['EI'], FUZZY['FI']],
    [FUZZY['FI'], FUZZY['EI'], FUZZY['WI'], FUZZY['EI']])

# C3: best=C31 (Sustainable packaging), worst=C33
wS_C3, _ = solve_fbwm(
    [FUZZY['EI'], FUZZY['WI'], FUZZY['FI']],
    [FUZZY['FI'], FUZZY['EI'], FUZZY['EI']])

# C4: best=C44 (Eco transport), worst=C43
wS_C4, _ = solve_fbwm(
    [FUZZY['EI'], FUZZY['WI'], FUZZY['FI'], FUZZY['EI']],
    [FUZZY['WI'], FUZZY['EI'], FUZZY['EI'], FUZZY['FI']])

# C5: best=C53 (Sustainable use), worst=C52
wS_C5, _ = solve_fbwm(
    [FUZZY['EI'], FUZZY['FI'], FUZZY['EI']],
    [FUZZY['WI'], FUZZY['EI'], FUZZY['FI']])

# ── GLOBAL WEIGHTS = criteria_weight × sub_criteria_weight ──────────
gw_A = np.concatenate([
    wC_A[0]*wS_C1, wC_A[1]*wS_C2, wC_A[2]*wS_C3,
    wC_A[3]*wS_C4, wC_A[4]*wS_C5
])

ranks_A = pd.Series(gw_A, index=SUB_LABELS).rank(ascending=False).astype(int)
CR_A    = xi_A / CI_TABLE['VI']

print(f'Scenario A  │  CR = {CR_A:.4f}  (threshold ≤ 0.10)  → {"PASS" if CR_A<=0.1 else "FAIL"}')
print(f'Criteria weights: {dict(zip(CRIT_NAMES, np.round(wC_A,4)))}\n')
```

```
df_A = pd.DataFrame({'Global weight': np.round(gw_A,4), 'Rank': ranks_A},
                    index=SUB_LABELS).sort_values('Rank')
print('Top-6 sub-criteria (Scenario A):')
print(df_A.head(6).to_string())
```

```
Scenario A  │  CR = 0.0268  (threshold ≤ 0.10)  → PASS
Criteria weights: {'C1-Supplier': np.float64(0.1745), 'C2-Product': np.float64(0.3538), 'C3-Packaging': np.float64(0.1769), 'C4-Logistics': np.float64(0.1179), 'C5-Consumption': np.float64(0.1769)}

Top-6 sub-criteria (Scenario A):
                           Global weight  Rank
C23-Design for reuse              0.1190     1
C22-Modular design                0.1158     2
C32-Multipurpose packaging        0.0872     3
C51-Consumer mindset              0.0708     4
C52-Recovery data                 0.0708     4
C24-Energy reduction              0.0595     6
```

Step 4: Scenario B: GenAI Low adoption (21 sub-criteria)

```
# — CRITERIA LEVEL – 6 criteria, C6 (GenAI) ranked fairly important ————
best_crit_B  = [FUZZY['WI'], FUZZY['EI'], FUZZY['FI'], FUZZY['VI'], FUZZY['FI'], FUZZY['FI']]
worst_crit_B = [FUZZY['FI'], FUZZY['VI'], FUZZY['EI'], FUZZY['EI'], FUZZY['EI'], FUZZY['WI']]
wC_B, xi_B   = solve_fbwm(best_crit_B, worst_crit_B)

# — C6 sub-criteria (GenAI LOW): best=C62 (non-interactive KS), worst=C63 ——
wS_C6_B, _ = solve_fbwm(
    [FUZZY['WI'], FUZZY['EI'], FUZZY['FI']],
    [FUZZY['FI'], FUZZY['WI'], FUZZY['EI']])

gw_B = np.concatenate([
    wC_B[0]*wS_C1, wC_B[1]*wS_C2, wC_B[2]*wS_C3,
    wC_B[3]*wS_C4, wC_B[4]*wS_C5, wC_B[5]*wS_C6_B
])

ranks_B = pd.Series(gw_B, index=SUB_LABELS_21).rank(ascending=False).astype(int)
CR_B    = xi_B / CI_TABLE['AI']

print(f'Scenario B  |  CR = {CR_B:.4f}  (threshold ≤ 0.10)  → {"PASS" if CR_B<=0.1 else "FAIL"}')
print(f'C6-GenAI criteria weight: {wC_B[5]:.4f}')
print(f'C6 sub-weights: C61={wS_C6_B[0]:.4f}, C62={wS_C6_B[1]:.4f}, C63={wS_C6_B[2]:.4f}\n')

df_B = pd.DataFrame({'Global weight': np.round(gw_B,4), 'Rank': ranks_B},
                    index=SUB_LABELS_21).sort_values('Rank')
print('Top-6 sub-criteria (Scenario B):')
print(df_B.head(6).to_string())
```

```
Scenario B  |  CR = 0.0190  (threshold ≤ 0.10)  → PASS
C6-GenAI criteria weight: 0.1486
C6 sub-weights: C61=0.2474, C62=0.5017, C63=0.2509

Top-6 sub-criteria (Scenario B):
                           Global weight  Rank
C23-Design for reuse              0.1013     1
C22-Modular design                0.0986     2
C62-Non-interactive KS            0.0745     3
C32-Multipurpose packaging        0.0743     4
C52-Recovery data                 0.0602     5
C51-Consumer mindset              0.0602     5
```

Step 5: Scenario C- GenAI High adoption (21 sub-criteria)

```
# — CRITERIA LEVEL – C6 now second most important ——————————————————————
best_crit_C  = [FUZZY['FI'], FUZZY['EI'], FUZZY['VI'], FUZZY['AI'], FUZZY['VI'], FUZZY['WI']]
worst_crit_C = [FUZZY['VI'], FUZZY['AI'], FUZZY['FI'], FUZZY['EI'], FUZZY['FI'], FUZZY['FI']]
wC_C, xi_C   = solve_fbwm(best_crit_C, worst_crit_C)

# — C6 sub-criteria (GenAI HIGH): best=C61 (interactive KS), most valued ————
wS_C6_C, _ = solve_fbwm(
    [FUZZY['EI'], FUZZY['WI'], FUZZY['VI']],
    [FUZZY['VI'], FUZZY['FI'], FUZZY['EI']])

gw_C = np.concatenate([
    wC_C[0]*wS_C1, wC_C[1]*wS_C2, wC_C[2]*wS_C3,
    wC_C[3]*wS_C4, wC_C[4]*wS_C5, wC_C[5]*wS_C6_C
])

ranks_C = pd.Series(gw_C, index=SUB_LABELS_21).rank(ascending=False).astype(int)
CR_C    = xi_C / CI_TABLE['AI']

print(f'Scenario C  |  CR = {CR_C:.4f}  (threshold ≤ 0.10)  → {"PASS" if CR_C<=0.1 else "FAIL"}')
print(f'C6-GenAI criteria weight: {wC_C[5]:.4f}')
print(f'C6 sub-weights: C61={wS_C6_C[0]:.4f}, C62={wS_C6_C[1]:.4f}, C63={wS_C6_C[2]:.4f}\n')

df_C = pd.DataFrame({'Global weight': np.round(gw_C,4), 'Rank': ranks_C},
                    index=SUB_LABELS_21).sort_values('Rank')
print('Top-6 sub-criteria (Scenario C):')
print(df_C.head(6).to_string())
```

```
Scenario C  |  CR = 0.0321  (threshold ≤ 0.10)  → PASS
C6-GenAI criteria weight: 0.1290
C6 sub-weights: C61=0.2768, C62=0.5387, C63=0.1845

Top-6 sub-criteria (Scenario C):
                           Global weight  Rank
C23-Design for reuse              0.1302     1
C22-Modular design                0.1267     2
C62-Non-interactive KS            0.0695     3
C24-Energy reduction              0.0651     4
C21-CE product design             0.0651     4
C32-Multipurpose packaging        0.0636     6
```

Step 6: Full comparison table (all 21 sub-criteria)

```python
df_full = pd.DataFrame({
    'Sc-A weight': np.round(np.append(gw_A, [np.nan,np.nan,np.nan]), 4),
    'Sc-A rank'  : list(ranks_A.values) + ['—','—','—'],
    'Sc-B weight': np.round(gw_B, 4),
    'Sc-B rank'  : ranks_B.values,
    'Sc-C weight': np.round(gw_C, 4),
    'Sc-C rank'  : ranks_C.values,
}, index=SUB_LABELS_21)

# Rank shift column (A→C, for original 18 only)
shifts = []
for i in range(21):
    if i < 18:
        shifts.append(int(ranks_A.iloc[i]) - int(ranks_C.iloc[i]))
    else:
        shifts.append('New')
df_full['Rank shift (A→C)'] = shifts

print('=== FULL RESULTS TABLE ===')
pd.set_option('display.max_colwidth', 30)
print(df_full.to_string())
```

```
=== FULL RESULTS TABLE ===
                           Sc-A weight Sc-A rank  Sc-B weight  Sc-B rank  Sc-C weight  Sc-C rank Rank shift (A→C)
C11-Supplier compatible         0.0197        17       0.0168         20       0.0146         20               -3
C12-Eco raw materials           0.0590         8       0.0503          9       0.0437          9               -1
C13-Env regulations             0.0574         9       0.0489         10       0.0425         10               -1
C14-Clean technologies          0.0383        13       0.0326         16       0.0283         15               -2
C21-CE product design           0.0595         6       0.0507          7       0.0651          4                2
C22-Modular design              0.1158         2       0.0986          2       0.1267          2                0
C23-Design for reuse            0.1190         1       0.1013          1       0.1302          1                0
C24-Energy reduction            0.0595         6       0.0507          7       0.0651          4                2
C31-Sustainable packaging       0.0448        10       0.0382         11       0.0327         13               -3
C32-Multipurpose packaging      0.0872         3       0.0743          4       0.0636          6               -3
C33-Recyclable packaging        0.0448        10       0.0382         11       0.0327         13               -3
C41-Reverse logistics           0.0295        15       0.0251         18       0.0242         17               -2
C42-Remanufacturing             0.0442        12       0.0377         13       0.0363         11                1
C43-Waste management            0.0295        15       0.0251         18       0.0242         17               -2
C44-Eco transport               0.0147        18       0.0126         21       0.0121         21               -3
C51-Consumer mindset            0.0708         4       0.0602          5       0.0516          7               -3
C52-Recovery data               0.0708         4       0.0602          5       0.0516          7               -3
C53-Sustainable use             0.0354        14       0.0301         17       0.0258         16               -2
C61-Interactive KS                 NaN         —       0.0368         15       0.0357         12              New
C62-Non-interactive KS             NaN         —       0.0745          3       0.0695          3              New
C63-Org enablers                   NaN         —       0.0373         14       0.0238         19              New
```

Step 7: Consistency ratio summary

```python
cr_summary = pd.DataFrame({
    'Scenario'       : ['A – Baseline','B – GenAI Low','C – GenAI High'],
    'ξ* (optimal)'   : [round(xi_A,4), round(xi_B,4), round(xi_C,4)],
    'CI used'         : [CI_TABLE['VI'], CI_TABLE['AI'], CI_TABLE['AI']],
    'CR = ξ*/CI'      : [round(CR_A,4), round(CR_B,4), round(CR_C,4)],
    'Status'          : ['√ PASS' if r<=0.1 else 'X FAIL' for r in [CR_A,CR_B,CR_C]],
})
print(cr_summary.to_string(index=False))
print('\nAll CR < 0.10 → expert judgements are consistent.')
```

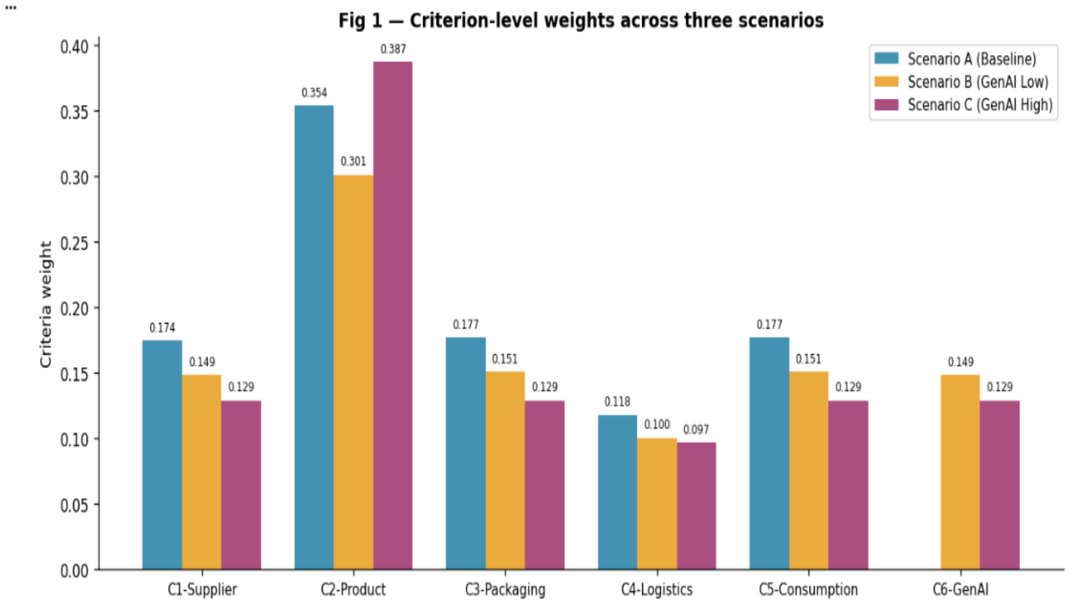
```
      Scenario  ξ* (optimal)  CI used  CR = ξ*/CI Status
  A – Baseline        0.1793     6.69      0.0268 √ PASS
 B – GenAI Low        0.1527     8.04      0.0190 √ PASS
C – GenAI High        0.2581     8.04      0.0321 √ PASS

All CR < 0.10 → expert judgements are consistent.
```

Step 8: Visualisations

8(i) Criteria-level weight

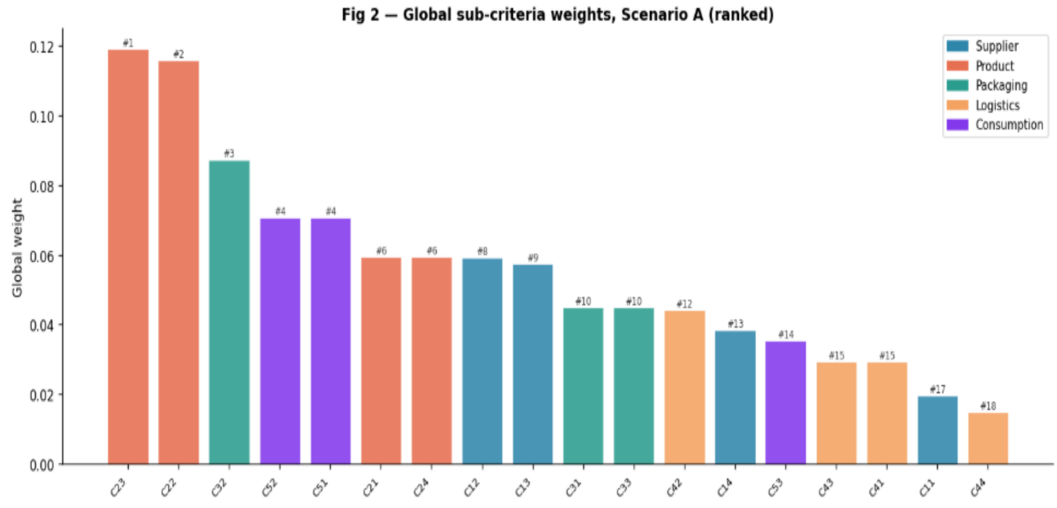
```python
COLORS = {'A':'#2E86AB', 'B':'#E9A227', 'C':'#A23B72'}

# ── Fig 1: Criteria-level weights ──────────────────────────────
fig, ax = plt.subplots(figsize=(11,5))
x = np.arange(6)
w = 0.26
ax.bar(x[:5]-w, wC_A, w, label='Scenario A (Baseline)', color=COLORS['A'], alpha=0.9)
ax.bar(x-0,     wC_B, w, label='Scenario B (GenAI Low)', color=COLORS['B'], alpha=0.9)
ax.bar(x+w,     wC_C, w, label='Scenario C (GenAI High)', color=COLORS['C'], alpha=0.9)
ax.set_xticks(x)
ax.set_xticklabels(['C1-Supplier','C2-Product','C3-Packaging',
                    'C4-Logistics','C5-Consumption','C6-GenAI'], fontsize=9)
ax.set_ylabel('Criteria weight')
ax.set_title('Fig 1 – Criterion-level weights across three scenarios', fontweight='bold')
ax.legend(fontsize=9)
for bar in ax.patches:
    if bar.get_height() > 0.01:
        ax.text(bar.get_x()+bar.get_width()/2, bar.get_height()+0.005,
                f'{bar.get_height():.3f}', ha='center', va='bottom', fontsize=7)
```

```
                 'C4-Logistics', 'C5-Consumption', 'C6-GenAI'], fontsize=9)
ax.set_ylabel('Criteria weight')
ax.set_title('Fig 1 — Criterion-level weights across three scenarios', fontweight='bold')
ax.legend(fontsize=9)
for bar in ax.patches:
    if bar.get_height() > 0.01:
        ax.text(bar.get_x()+bar.get_width()/2, bar.get_height()+0.005,
                f'{bar.get_height():.3f}', ha='center', va='bottom', fontsize=7)
plt.tight_layout()
plt.savefig('charts/fig1_criteria_weights.png', dpi=150, bbox_inches='tight')
plt.show()
```



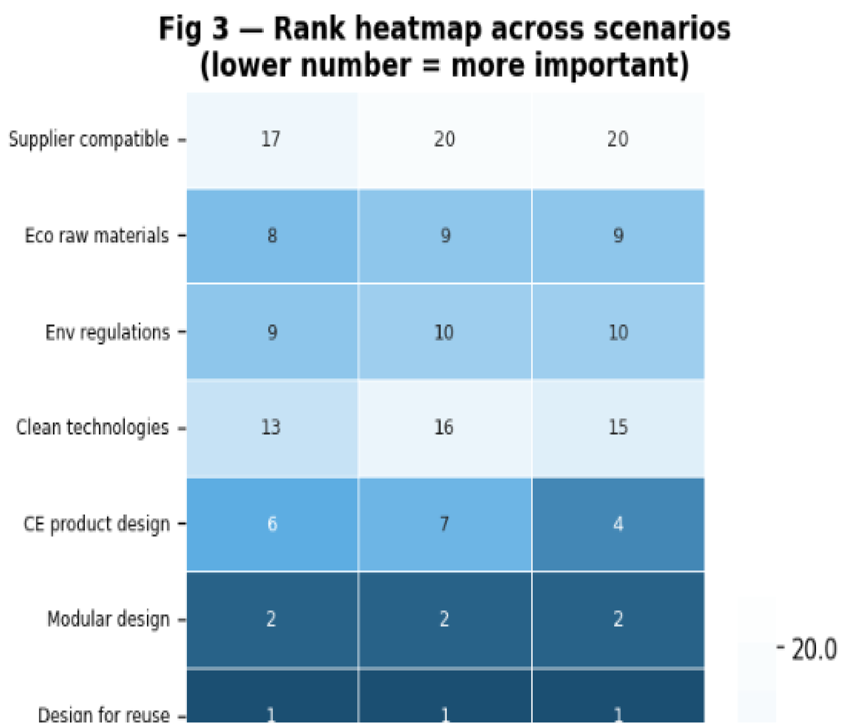
8(ii) Global sub-criteria weights- Scenario A

```python
# — Fig 2: Global sub-criteria weights – Scenario A ————————————————
fig, ax = plt.subplots(figsize=(13,5))
crit_colors = ['#2E86AB']*4+['#E76F51']*4+['#2A9D8F']*3+['#F4A261']*4+['#8338EC']*3
sorted_idx  = np.argsort(gw_A)[::-1]
bars = ax.bar(range(18), gw_A[sorted_idx], color=np.array(crit_colors)[sorted_idx],
              alpha=0.88, edgecolor='white', linewidth=0.5)
ax.set_xticks(range(18))
ax.set_xticklabels([SUB_LABELS[i].split('-')[0] for i in sorted_idx], rotation=45, ha='right', fontsize=8)
ax.set_ylabel('Global weight')
ax.set_title('Fig 2 – Global sub-criteria weights, Scenario A (ranked)', fontweight='bold')
patches = [
    mpatches.Patch(color='#2E86AB', label='Supplier'),
    mpatches.Patch(color='#E76F51', label='Product'),
    mpatches.Patch(color='#2A9D8F', label='Packaging'),
    mpatches.Patch(color='#F4A261', label='Logistics'),
    mpatches.Patch(color='#8338EC', label='Consumption'),
]
ax.legend(handles=patches, fontsize=9, loc='upper right')
for i,(bar,idx) in enumerate(zip(bars,sorted_idx)):
    ax.text(bar.get_x()+bar.get_width()/2, bar.get_height()+0.001,
            f'#{int(ranks_A.iloc[idx])}', ha='center', fontsize=7, color='#333')
plt.tight_layout()
plt.savefig('charts/fig2_global_weights_A.png', dpi=150, bbox_inches='tight')
plt.show()
```



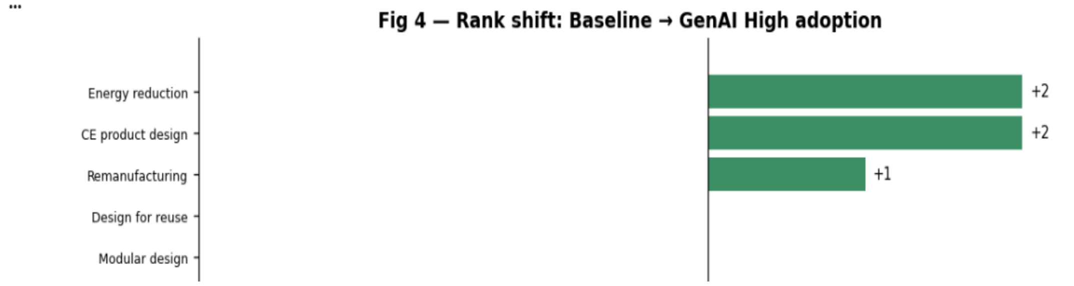
*8(iii) Rank Heatmap (all 21 sub-criteria * 3 scenarios)*

```python
# — Fig 3: Rank heatmap (all 21 sub-criteria × 3 scenarios) ──────────
rank_matrix = pd.DataFrame({
    'Sc-A': list(ranks_A.values)+[np.nan,np.nan,np.nan],
    'Sc-B': list(ranks_B.values),
    'Sc-C': list(ranks_C.values),
}, index=SUB_LABELS_21)

fig, ax = plt.subplots(figsize=(6,11))
cmap = LinearSegmentedColormap.from_list('rnk',
    ['#1B4F72','#5DADE2','#AED6F1','#EBF5FB','#FDFEFE'], N=21)
sns.heatmap(rank_matrix.astype(float), ax=ax, cmap=cmap,
            annot=True, fmt='.0f', linewidths=0.4,
            cbar_kws={'label':'Rank (1=most important)','shrink':0.5},
            annot_kws={'size':8}, vmin=1, vmax=21)
ax.set_title('Fig 3 — Rank heatmap across scenarios\n(lower number = more important)',
             fontweight='bold')
ax.set_xticklabels(['Baseline','GenAI Low','GenAI High'], fontsize=9)
ax.set_yticklabels([l.split('-',1)[-1] for l in SUB_LABELS_21], rotation=0, fontsize=7.5)
plt.tight_layout()
plt.savefig('charts/fig3_rank_heatmap.png', dpi=150, bbox_inches='tight')
plt.show()
```



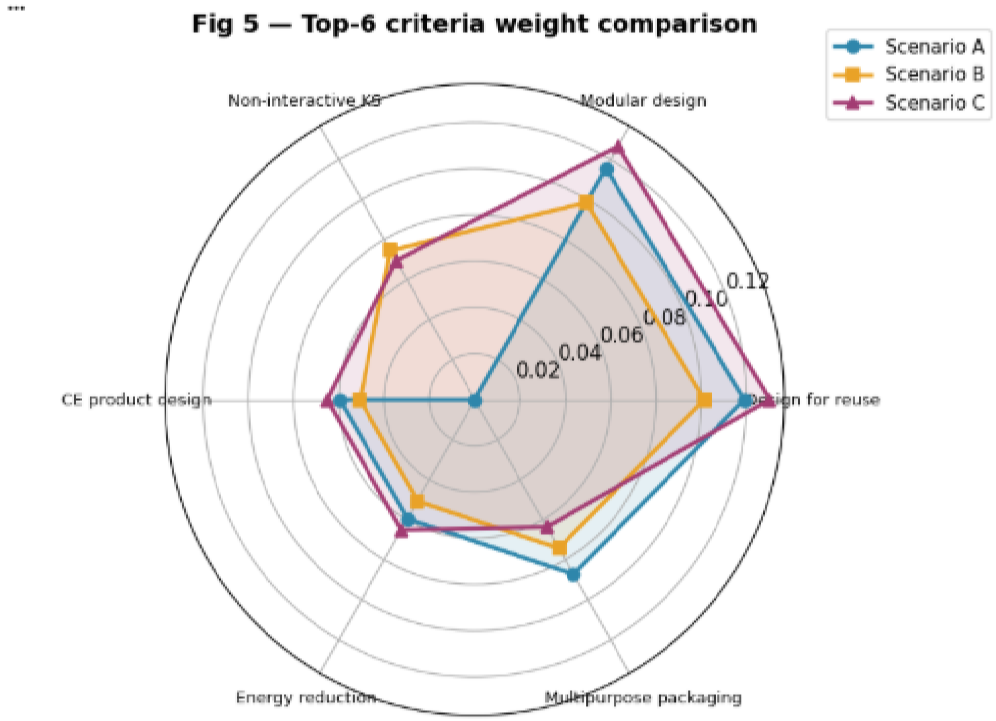
8(iv) Tornado-rank shift Baseline → GenAI High

```
# — Fig 4: Tornado – rank shift Baseline → GenAI High ————————————
rc_data = [(lbl, int(ranks_A.iloc[i]), int(ranks_C.iloc[i]),
            int(ranks_A.iloc[
          for i,lbl in enumer (function) columns: Axes | None
rc_df = pd.DataFrame(rc_data, columns=['label','rankA','rankC','improvement'])
rc_df = rc_df.sort_values('improvement')

fig, ax = plt.subplots(figsize=(10,7))
colors_tor = ['#C0392B' if v<0 else ('#1A7A4A' if v>0 else '#888') for v in rc_df['improvement']]
ax.barh(rc_df['label'], rc_df['improvement'], color=colors_tor, alpha=0.85)
ax.axvline(0, color='black', linewidth=0.8)
ax.set_xlabel('Rank improvement (A→C)  [positive = rose in importance]')
ax.set_title('Fig 4 – Rank shift: Baseline → GenAI High adoption',
            fontweight='bold')
ax.set_yticklabels([l.split('-',1)[-1] for l in rc_df['label']], fontsize=8)
for bar,val in zip(ax.patches, rc_df['improvement']):
    if val != 0:
        ax.text(bar.get_width()+(0.05 if val>0 else -0.05),
                bar.get_y()+bar.get_height()/2,
                f'{int(val):+d}', va='center',
                ha='left' if val>0 else 'right', fontsize=9)
plt.tight_layout()
plt.savefig('charts/fig4_tornado.png', dpi=150, bbox_inches='tight')
plt.show()
```



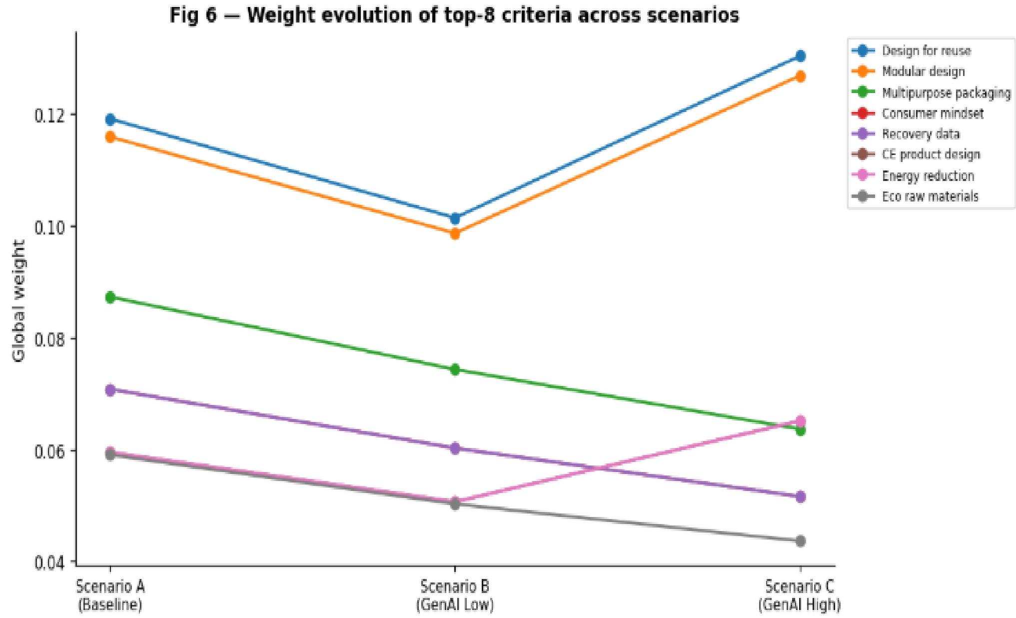
8(v) Radar Chart-Top 6 criteria across scenarios

```python
# ── Fig 5: Radar chart — top-6 criteria across scenarios ──────────────────
top6 = ['C23-Design for reuse','C22-Modular design','C62-Non-interactive KS',
        'C21-CE product design','C24-Energy reduction','C32-Multipurpose packaging']
N = 6
angles = np.linspace(0, 2*np.pi, N, endpoint=False).tolist(); angles += angles[:1]

def get_w(arr, lbl_list, top):
    return [float(arr[illegible]st else 0 for t in top]
              (constant) SUB_LABELS: list[str]

vals_A = get_w(gw_A, SUB_LABELS,    top6); vals_A += vals_A[:1]
vals_B = get_w(gw_B, SUB_LABELS_21, top6); vals_B += vals_B[:1]
vals_C = get_w(gw_C, SUB_LABELS_21, top6); vals_C += vals_C[:1]

fig, ax = plt.subplots(figsize=(7,7), subplot_kw=dict(polar=True))
for vals, label, color, marker in [
    (vals_A, 'Scenario A', COLORS['A'], 'o'),
    (vals_B, 'Scenario B', COLORS['B'], 's'),
    (vals_C, 'Scenario C', COLORS['C'], '^'),
]:
    ax.plot(angles, vals, marker+'-', lw=2, color=color, label=label)
    ax.fill(angles, vals, alpha=0.12, color=color)
ax.set_thetagrids(np.degrees(angles[:-1]),
                  [l.split('-',1)[-1] for l in top6], fontsize=8)
ax.set_title('Fig 5 — Top-6 criteria weight comparison', fontweight='bold', pad=25)
ax.legend(loc='upper right', bbox_to_anchor=(1.35,1.1), fontsize=9)
plt.tight_layout()
plt.savefig('charts/fig5_radar.png', dpi=150, bbox_inches='tight')
plt.show()
```



8(vi) Weight evaluation across scenarios (line)

```
# — Fig 6: Weight evolution across scenarios (line) ————————————————
track8 = ['C23-Design for reuse','C22-Modular design','C32-Multipurpose packaging',
          'C51-Consumer mindset','C52-Recovery data','C21-CE product design',
          'C24-Energy reduction','C12-Eco raw materials']

fig, ax = plt.subplots(figsize=(10,5))
for lbl in track8:
    wa = float(gw_A[SUB_LABELS.index(lbl)])    if lbl in SUB_LABELS    else 0
    wb = float(gw_B[SUB_LABELS_21.index(lbl)]) if lbl in SUB_LABELS_21 else 0
    wc = float(gw_C[SUB_LABELS_21.index(lbl)]) if lbl in SUB_LABELS_21 else 0
    ax.plot([0,1,2],[wa,wb,wc], 'o-', label=lbl.split('-',1)[-1],
            linewidth=1.8, markersize=6)

ax.set_xticks([0,1,2])
ax.set_xticklabels(['Scenario A\n(Baseline)','Scenario B\n(GenAI Low)',
                    'Scenario C\n(GenAI High)'], fontsize=9)
ax.set_ylabel('Global weight')
ax.set_title('Fig 6 — Weight evolution of top-8 criteria across scenarios', fontweight='bold')
ax.legend(fontsize=7.5, bbox_to_anchor=(1.01,1), loc='upper left')
plt.tight_layout()
plt.savefig('charts/fig6_weight_evolution.png', dpi=150, bbox_inches='tight')
plt.show()
print('All 6 figures saved to charts/ folder.')
```




```
All 6 figures saved to charts/ folder.
```

Step 9: Export to Excel;

```
*Sheet1: Global weights all scenarios
*Sheet2: Criteria Weights
*Sheet3: CR Summary
*Sheet4: Charts
```

#all file will be downloaded in excel

```python
from openpyxl import Workbook
from openpyxl.styles import Font, PatternFill, Alignment, Border, Side
from openpyxl.drawing.image import Image as XLImage
from openpyxl.utils import get_column_letter

def hdr(text, row, col, ws, span=1, fill='1B4F72', fsize=11):
    c = ws.cell(row=row, column=col, value=text)
    c.font  = Font(bold=True, color='FFFFFF', size=fsize, name='Arial')
    c.fill  = PatternFill('solid', fgColor=fill)
    c.alignment = Alignment(horizontal='center', vertical='center')
    if span > 1:
        ws.merge_cells(start_row=row, start_column=col,
                       end_row=row, end_column=col+span-1)

def cell(ws, row, col, val, bold=False, fmt=None, align='center', color=None, fill_col=None):
    c = ws.cell(row=row, column=col, value=val)
    c.font  = Font(bold=bold, size=9, name='Arial', color=color or '000000')
    c.alignment = Alignment(horizontal=align, vertical='center')
    if fmt:      c.number_format = fmt
    if fill_col: c.fill = PatternFill('solid', fgColor=fill_col)
    return c

def rank_fill(r):
    if r<=3: return 'C8E6C9'
    if r<=6: return 'FFF9C4'
    if r<=10: return 'FFEEBA'
    return 'FFFFFF'

wb = Workbook()
```

```python
# — Sheet 1: Global weights all scenarios ——————————————————————
ws = wb.active; ws.title = 'Global_Weights'
for col,w in enumerate([3,30,13,10,13,10,13,10,15],start=1):
    ws.column_dimensions[get_column_letter(col)].width=w

hdr('Global sub-criteria weights and ranks — all scenarios',1,2,ws,span=8)
for j,h in enumerate(['Sub-criterion','Sc-A weight','Sc-A rank',
                       'Sc-B weight','Sc-B rank','Sc-C weight','Sc-C rank','Rank shift']):
    c=ws.cell(row=2,column=j+2,value=h)
    c.font=Font(bold=True,size=9,name='Arial',color='FFFFFF')
    c.fill=PatternFill('solid',fgColor='2E86AB')
    c.alignment=Alignment(horizontal='center')

for i,lbl in enumerate(SUB_LABELS_21):
    r=3+i; ws.row_dimensions[r].height=20
    cell(ws,r,2,lbl,align='left')
    if i<18:
        cell(ws,r,3,round(gw_A[i],4),fmt='0.0000',align='center')
        ra=int(ranks_A.iloc[i])
        cell(ws,r,4,ra,bold=True,align='center',fill_col=rank_fill(ra))
        shift=int(ranks_A.iloc[i])-int(ranks_C.iloc[i])
        shift_str=f'+{shift}' if shift>0 else (str(shift) if shift<0 else '0')
        cell(ws,r,9,shift_str,align='center',bold=True,
             color='1A7A4A' if shift>0 else ('C0392B' if shift<0 else '888888'))
    else:
        cell(ws,r,3,'—',align='center',color='AAAAAA')
        cell(ws,r,4,'N/A',align='center',color='AAAAAA')
        cell(ws,r,9,'New',align='center',bold=True,color='1B4F72')
    cell(ws,r,5,round(gw_B[i],4),fmt='0.0000',align='center')
    rb=int(ranks_B.iloc[i])
    cell(ws,r,6,rb,bold=True,align='center',fill_col=rank_fill(rb))
    cell(ws,r,7,round(gw_C[i],4),fmt='0.0000',align='center')
    rc_=int(ranks_C.iloc[i])
    cell(ws,r,8,rc_,bold=True,align='center',fill_col=rank_fill(rc_))
    if i%2==0:
        for col in [2,3,5,7,9]:
            ws.cell(r,col).fill=PatternFill('solid',fgColor='F8F9FA')
```

```python
# — Sheet 2: Criteria weights ————————————————————————————————
ws2=wb.create_sheet('Criteria_Weights')
hdr('Criteria-level weights across scenarios',1,1,ws2,span=7)
for j,h in enumerate(['Criterion','Sc-A','Sc-A rank','Sc-B','Sc-B rank','Sc-C','Sc-C rank']):
    c=ws2.cell(row=2,column=j+1,value=h)
    c.font=Font(bold=True,size=9,name='Arial',color='FFFFFF')
    c.fill=PatternFill('solid',fgColor='2E86AB')
    c.alignment=Alignment(horizontal='center')
crit_ranks_A=pd.Series(wC_A).rank(ascending=False).astype(int).tolist()
crit_ranks_B=pd.Series(wC_B).rank(ascending=False).astype(int).tolist()
crit_ranks_C=pd.Series(wC_C).rank(ascending=False).astype(int).tolist()
for i,(cn,wa,wb_,wc) in enumerate(zip(
    CRIT_NAMES6,
    list(wC_A)+[None],list(wC_B),list(wC_C))):
    r=3+i
    ws2.cell(r,1,cn).font=Font(size=9,bold=True,name='Arial')
    if wa is not None:
        cell(ws2,r,2,round(wa,4),fmt='0.0000'); cell(ws2,r,3,crit_ranks_A[i],bold=True)
    else:
        cell(ws2,r,2,'—',color='AAAAAA'); cell(ws2,r,3,'N/A',color='AAAAAA')
    cell(ws2,r,4,round(wb_,4),fmt='0.0000'); cell(ws2,r,5,crit_ranks_B[i],bold=True)
    cell(ws2,r,6,round(wc,4),fmt='0.0000');  cell(ws2,r,7,crit_ranks_C[i],bold=True)

# — Sheet 3: CR Summary ————————————————————————————————————
ws3=wb.create_sheet('CR_Summary')
hdr('Consistency ratio summary',1,1,ws3,span=5)
for j,h in enumerate(['Scenario','xi*','CI','CR','Status']):
    c=ws3.cell(2,j+1,h); c.font=Font(bold=True,size=9,name='Arial',color='FFFFFF')
    c.fill=PatternFill('solid',fgColor='2E86AB'); c.alignment=Alignment(horizontal='center')
for i,(sc,xi,ci,cr) in enumerate([('A – Baseline',xi_A,CI_TABLE['VI'],CR_A),
                                  ('B – GenAI Low',xi_B,CI_TABLE['AI'],CR_B),
                                  ('C – GenAI High',xi_C,CI_TABLE['AI'],CR_C)]):
    r=3+i
    ws3.cell(r,1,sc).font=Font(size=9,name='Arial')
    for j,v in enumerate([round(xi,4),ci,round(cr,4)]):
        c=ws3.cell(r,j+2,v); c.number_format='0.0000'
        c.font=Font(size=9,name='Arial'); c.alignment=Alignment(horizontal='center')
    status='✓ PASS' if cr<=0.1 else '✗ FAIL'
    c=ws3.cell(r,5,status); c.font=Font(bold=True,size=9,name='Arial',
        color='1A7A4A' if cr<=0.1 else 'C0392B')
    c.alignment=Alignment(horizontal='center')
    if cr<=0.1: c.fill=PatternFill('solid',fgColor='C8E6C9')
```

```python
# ── Sheet 4: Charts ──────────────────────────────────────────────────────
ws4=wb.create_sheet('Charts')
hdr('Visualisation charts',1,1,ws4,span=10)
chart_files=[
    ('charts/fig1_criteria_weights.png','Fig 1 – Criteria weights',2),
    ('charts/fig2_global_weights_A.png','Fig 2 – Global weights Sc-A',36),
    ('charts/fig3_rank_heatmap.png',   'Fig 3 – Rank heatmap',70),
    ('charts/fig4_tornado.png',         'Fig 4 – Rank shift tornado',115),
    ('charts/fig5_radar.png',           'Fig 5 – Radar chart',157),
    ('charts/fig6_weight_evolution.png','Fig 6 – Weight evolution',195),
]
for fpath,title,sr in chart_files:
    ws4.cell(sr,1,title).font=Font(bold=True,size=10,name='Arial',color='1B4F72')
    try:
        img=XLImage(fpath); img.anchor=f'A{sr+1}'; ws4.add_image(img)
    except: pass

out='HFBWM_GenAI_GreenValue_Results.xlsx'
wb.save(out)
print(f'Excel saved → {out}')

# Download in Colab
try:
    from google.colab import files
    files.download(out)
    print('Download triggered.')
except:
    print(f'File saved locally as: {out}')
```

```
Excel saved → HFBWM_GenAI_GreenValue_Results.xlsx
Download triggered.
```