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ORIGINAL ARTICLE

# Fostering lithium-ion battery remanufacturing through Industry 5.0

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**Abstract**

The rise of electric vehicles (EVs) has resulted in notable environmental benefits, yet challenges persist regarding battery disposal and recovery. The increasing demand for EVs heightens concerns about the environmental impact of lithium-ion battery (LIB) waste, which threatens both ecosystems and public health. Although remanufacturing is seen as a sustainable solution to these issues, current research does not thoroughly examine the role of Industry 5.0 technologies in optimising this process. This study aims to compare and assess the potential of various Industry 5.0 technologies and approaches to enhance the remanufacturing of lithium-ion batteries. Using the AHP-PROMETHEE method, we identify the most critical and influential Industry 5.0 prospects that should be prioritised for addressing key challenges such as diagnostic accuracy, safe disassembly, and high-quality reassembly. The multi-criteria analysis highlights key Industry 5.0 imperatives that can facilitate efficient and effective remanufacturing processes. The study identifies Digital Product Passport (DPP), Digital Twin (DT), and the Internet of Everything (IoE) as critical enablers in optimizing the LIB remanufacturing process. The analysis reveals that DPP stands out as the top enabler, significantly enhancing transparency, traceability, and lifecycle management for LIBs. DT and IoE follow closely, contributing to real-time monitoring, predictive maintenance, and seamless data integration across the supply chain. This paper delves in the emerging concept of the Digital Battery Passport (DBP), a DPP mandated by recent European regulations aimed at improving battery management and circularity. The DBP facilitates access to critical data throughout the battery's lifecycle, including its origin, composition, and state of health. This information is crucial for optimising remanufacturing processes, ensuring compliance with sustainability standards, and extending battery life. The paper highlights the potential of DBP to transform the EV battery value chain by enhancing transparency and enabling more informed decision-making across stakeholders. Our findings offer significant insights for policymakers, battery manufacturers, and remanufacturing firms.

**Keywords** Remanufacturing · Electric vehicles · Lithium-ion battery · Sustainability · Industry 5.0 · Digital battery passport

## 1 Introduction

Because of its emissions, the transport sector is seen as having one of the biggest effects on the environment on Earth. Electrification and Electric Vehicles (EVs) can help decarbonise transportation by promoting low- and zero-emission automobiles. Consequently, global legislation aimed at reducing carbon emissions, environmental concerns, and technological advancements in the automobile industry with respect to electrification have caused a boom in BEV sales, which are expected to reach 17 million units in 2024 [1–3].

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The rising demand for EVs has led to a significant increase in the production of Lithium-Ion Batteries (LIBs). Worldwide demand for the batteries is predicted to increase and is now doing so. By 2025, the disposal of batteries might result in between 250,000 and 350,000 tonnes of garbage-a significant amount of waste that is still valuable [4, 5]. Over time, batteries deteriorate, and Original Equipment Manufacturers (OEMs) advise changing them when they are around 80% of the way to their initial capacity, at which point they are no longer functional. Unfortunately, the average lifespan of batteries is far less than that of traditional cars [6]. Recovering batteries can also alleviate the long lead times brought on by erratic and complex supply chains while reducing raw material extraction impacts and prolonging product lifespan [7, 8]. However, disposing of these batteries at the End-of-Life (EOL) poses substantial environmental challenges because of their hazardous components, such as heavy metals and toxic chemicals. To tackle this problem, remanufacturing has become a promising solution, reducing the environmental impact of LIB waste by recovering and refurbishing used batteries, thus extending their life cycle [9]. Three strategies are commonly recognised as circular strategies: recycling, remanufacturing, and reuse. Reuse can be considered direct or indirect, depending on the sector in which the second use is exploited. Recycling involves material recovery after disassembly to alleviate production impacts, promoting sustainability and resource efficiency. Remanufacturing is particularly advantageous because it allows batteries to be used in primary applications by replacing damaged cells, even if their condition is inadequate [10]. Additionally, remanufacturing can help decrease the need for producing new batteries, thereby reducing the environmental impact of the LIB market [11].

However, there is a significant gap in the current literature regarding how advanced technologies, specifically Industry 5.0 (I5.0) enablers, can optimise the LIB remanufacturing process. I5.0, which involves the convergence of industrial automation, digital technologies, and human worker inclusion, has the potential to revolutionise the remanufacturing process of LIBs. Recent literature has highlighted the relevant and disruptive methodological innovations of Industry 5.0 compared to Industry 4.0 [12–14]. However, considerable gaps remain in addressing the challenges of sustainable manufacturing, an area where few studies have been conducted [15]. Leveraging I5.0 enablers such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics can lead to more efficient and effective processes, resulting in reduced costs and improved sustainability. By adopting an I5.0 approach, remanufacturing companies can optimise their operations and minimise waste, while battery manufacturers can gain a competitive advantage by offering more sustainable products.

The purpose of this paper is to explore the potential of I5.0 in supporting the remanufacturing of LIBs from EVs. The objectives of this study are as follows:

1. Understand the current state of LIB remanufacturing and its challenges, while exploring the potential of I5.0 technologies for enhancement.
2. Understand the current state of LIB remanufacturing and its challenges, while exploring the potential of I5.0 technologies for enhancement.
3. Discuss results and provide future directions.

By achieving these objectives, this research aims to highlight the opportunities offered by I5.0 for improving the remanufacturing of LIBs, thereby contributing to sustainable manufacturing practices and the circular economy

Hence, this article first outlines the opportunities presented by Industry 5.0 and modern advancements for sustainable manufacturing practices and the circular economy, providing a theoretical foundation for this study. It also analyses the remanufacturing process for batteries to establish a context for the subsequent discussion. Finally, a discussion highlights current barriers and future research directions. The remainder of the study is structured as follows: Sect. 2 offers a comprehensive background on I5.0 and the remanufacturing process; Sect. 3 details the application of the AHP-PROMETHEE method to evaluate and prioritise I5.0 technologies for remanufacturing; Sect. 4 presents the study's findings; Sect. 5 examines the robustness of the results; and Sect. 6 and 7 provides final remarks and insights, highlighting future research directions.

## 2 Theoretical background

### 2.1 Remanufacturing process and issues

The rapid growth of the EV market leads to a corresponding increase in battery utilisation, resulting in material shortages, rising material prices, and EOL concerns. By 2030, discarded batteries are expected to retain 200 GWh of capacity, offering a substantial opportunity for circular business models [16, 17]. This is due to their typical service lifespan of 5–10 years, during which their energy capacity drops to around 80% of the initial capacity [18]. To optimise resource use and minimise waste through circular economy principles, a growing number of LIBs will become available for post-first-life applications, including reuse, remanufacturing, and recycling [19]. Reuse can involve reapplication in electric vehicles or repurposing for stationary, non-automotive applications. Recycling recovers valuable materials, reintegrating them into the value chain. Remanufacturing, which falls between reuse and recycling, focuses on restoring the entire product rather than just refurbishing or retrofitting individual components [20]. Some studies indicate that remanufacturing can be economically viable, saving about 40% compared to using new batteries [21].

Remanufacturing involves restoring LIBs so they can be reused in their original automotive applications. To be eligible for remanufacturing, batteries must demonstrate good State-of-Health (SOH) and meet all OEM specifications for power, energy, cycle life, and other criteria. Thereafter, inspection, partial disassembly of the battery packs, cleaning, replacement of any damaged cells or modules, reassembly, and quality testing are all part of the remanufacturing process for future use for further vehicle integration.

The collection facility begins the remanufacturing process by safely collecting all the dismissed batteries. Take back logistics must minimise risks since batteries are prone to thermal runway and explosion [9, 22]. Later, a visual assessment checks and sorts batteries considering surface defects [23].

SOH is the main parameter to evaluate battery suitability. Usually, SOH is defined as the reduction in capacity or the increase in internal resistance. Batteries in excellent condition can be used directly after SOH testing, whereas batteries in good condition can be repurposed. When conditions get worse, batteries undergo additional testing and disassembly. The testing methodologies involve estimating the SOH by measuring various parameters, such as impedance and internal resistance. These measurements offer insights into the degradation mechanisms that occur during battery ageing [4]. Given the complexity and time consumption of the diagnostic step, employing data-based methods that utilise machine learning techniques-such as cloud-based systems and digital twins-appears to be the most efficient way to calculate SOH and predict battery lifespan. By using data from sensors already installed in battery systems, these methods can maximise battery lifetime, reduce costs, and enhance the remanufacturing process [17, 20].

The disassembly process can be divided into several stages: opening the battery pack's shell in a controlled atmosphere to minimise cathode oxidation, removing the mechanical and electrical connections between cells, and removing auxiliary electronic components. Planning the disassembly of batteries involves several critical steps: generating an accurate representation of the item, planning several disassembly sequences, and identifying the optimal disassembly sequence and level [6]. For recycling or remanufacturing, battery packs are disassembled into modules, which are then individually tested. Modules found to be in good condition are sorted and reassembled into battery packs, while those in less optimal condition are further disassembled into individual cells. The cells are tested, and those in adequate condition are sorted and reassembled into modules, while those in poor condition are designated for final recycling. Disassembly entangles a series of economic and safety issues. Skills and equipment is mandatory to accomplish a dangerous process. In this step, the battery pack is opened in order to detach mechanical, electrical, and auxiliary electronic components [19]. Using robotic disassembly supported by cloud computing or a human–machine hybrid approach can reduce the risk of human accidents and lower remanufacturing costs [17, 24]. Additionally, virtual disassembly can optimise procedures and determine the most profitable stopping point [25]. After the pack with all the removable components has been opened, each cell is examined separately, and those that are found to be defective are replaced with ones that work with the others. To manage battery type variability and standardise the remanufacturing process, integrated designs for LIB parts should be developed, considering modularity, interfaces, and disassembly [19, 26].

The replacement of damaged components and final reassembly are steps that remanufacturing shares with the manufacturing process, potentially utilising the original production facility. Reassembly involves restoring structural integrity and reassembling components. Then, battery pack undergoes quality testing to ensure it meets all safety, performance, and durability standards from OEMs. The quality check accounts for electrical performance, thermal stability, and overall reliability. This underscores the importance of establishing a robust circular business model that involves the original battery manufacturers and key stakeholders in the EV value chain [2].

## 2.2 Industry 5.0 perspective

It is essential to first comprehend the foundation laid by Industry 4.0 (I4.0) in order to completely appreciate the benefits of I5.0. Originating in Germany, I4.0 is characterised by the implementation of Cyber-Physical Systems (CPS) to enhance manufacturing competitiveness [27]. By employing internet advancements it incorporates automation and digital technology to build smart factories. Digitalisation, the Internet of Things (IoT), robots, automated manufacturing, cloud computing, and artificial intelligence (AI) are among the core concepts [28, 29].

I4.0 and I5.0 are consecutive and parallel stages of industrial evolution. While I4.0 focuses on technology innovation and digital transformation, I5.0 expands on these concepts by incorporating resilience, sustainability, and human-centricity [30]. According to the European Commission, I5.0:

> complements the existing I4.0 paradigm by having research and innovation drive the transition to a sustainable, human-centric, and resilient European industry [31]

I5.0 emphasises collaboration between human workers and robots, harnessing human intelligence and creativity

[32]. It also aims to protect the environment through precise decision-making using predictive analytics and operational expertise, promoting both digital and green transitions [33, 34]. Moreover, I5.0 prioritises the well-being of industry employees, advocating for a human-centric and sustainable approach to industrial development [35]. Future factories should empower human operators both physically and intellectually, with robots assisting in strenuous tasks, cognitive systems offering decision-making support, mixed reality enhancing human vision and decisions, and co-intelligence facilitating mutual support between humans and robots [36]. Technologies should facilitate safe and efficient disassembly, predict battery health and optimise processes, support human decision-making with real-time insights, identify reusable and recyclable materials, and promote environmentally friendly operations. This section provides a comprehensive review of key prospects of I5.0 and their descriptions.

Additive Manufacturing (AM), also known as 3D printing, is a disruptive technology that allows for precision manufacturing with minimised waste and optimised resource utilisation. By facilitating the creation of complex geometries and reducing material consumption, AM supports sustainable production practices and enhances the customisation of products [37, 38]. Bio-inspired Technologies (BIT) complement AM by drawing inspiration from natural processes to develop materials and production methods that are environmentally friendly and sustainable. BIT focuses on sustainable and smart material usage, promoting recoverability and the reduction of environmental impact [39, 40].

Predictive Maintenance (PM) leverages data analytics and machine learning to foresee and prevent equipment failures, optimising operational sustainability and efficiency. By reducing downtime and extending the lifespan of machinery, PM contributes to more sustainable manufacturing processes [37]. Cloud Manufacturing (CM) enhances this by facilitating global collaboration and resource sharing through cloud computing. This decentralised approach promotes cooperation among distributed production units and optimises resource utilisation on a global scale [37]. Strategic placement of manufacturing units, or Strategic Unit Placement, further optimises efficiency by locating plants near raw materials or areas with lower costs, reducing transportation costs and enhancing supply chain efficiency [41].

Cognitive Cyber-physical Systems (CCPS) represent the convergence of physical processes and digital intelligence, enabling real-time adaptation to changes in demand and operational conditions. These systems enhance agility and intelligence in manufacturing operations, driving greater responsiveness and efficiency [37]. Man–Machine Symbiosis strengthens human cognition for safer and more productive interactions between humans and machines [42]. Collaborative Robots (Cobots), designed to work alongside human operators, optimise performance and reduce risks, fostering a positive human-robot relationship [37, 43]. Smart Wearables (SW) enhance productivity and worker safety by monitoring health and performance, providing data that can optimise work conditions [42]. Together, these technologies emphasise the human-centric approach of I5.0, aiming to create safer and more efficient work environments through advanced robotics and wearable technologies.

Blockchain Technology (BT) provides decentralised trust, secure transactions, transparency, and streamlined processes. In manufacturing, blockchain can track and verify the provenance of materials and products, ensuring data integrity and reducing fraud [37]. Digital Product Passports (DPP) complement blockchain by providing secure digital identities for products, facilitating life-cycle data management. This technology enhances traceability and accountability, supporting sustainability goals by ensuring proper documentation and tracking of product histories [43].

Virtual and Augmented Reality (VR/AR) technologies improve skill development and precision in inventory management by offering immersive training environments and real-time information overlays [41, 44]. Real Time Advisory systems enhance real-time information transfer and quality control, providing flexible operations and technical advice to optimise manufacturing processes [14, 43]. Next-generation Wireless Networks (5 G/6 G) enable faster, more reliable, and more efficient communication, ensuring seamless connectivity across manufacturing operations [41, 45].

Digital Twins (DT) serve as online emulation tools for system redesign, reconfiguration, and optimized operation. By creating virtual replicas of physical systems, digital twins enable detailed analysis and simulation, improving decision-making and operational efficiency [43]. The Industrial Metaverse (IM) further bridges real and virtual worlds, enabling interaction and influence across both realms. This technology facilitates advanced simulations, training, and virtual collaboration, driving innovation in manufacturing practices [46].

Edge Computing (EC) involves offloading tasks from the cloud to IoT devices at the network edge, reducing latency and enhancing service quality [47]. Edge IoT expands on this by providing low latency, high-quality services, extensive IoT infrastructure, and integrated AI to support real-time data processing and decision-making [48]. The Internet of Everything (IoE) promotes holistic connectivity and total integration, enabling efficient decision-making and operational transparency by connecting people, processes, and data [37, 49].

This section briefly reveals several important insights. Firstly, I5.0 necessitates a comprehensive approach to technological integration, concentrating on specific objectives, which goes beyond earlier modular approaches. Secondly, I5.0 leverages technology to attain sustainability and resource efficiency. Lastly, it merges human expertise with robotics

**Table 1** List of LIBs remanufacturing challenges

| Notation | Challenge | References |
|---|---|---|
| $C_1$ | Different shapes and features hinder standardised remanufacturing | [19, 26] |
| $C_2$ | Safe handling in take-back logistics | [9] |
| $C_3$ | Diagnostic and battery status tracking consume time and resources | [4, 17, 20] |
| $C_4$ | Safe and economic disassembly | [17, 24, 25] |
| $C_5$ | Efficient and high-quality reassembly | [2] |

to enhance decision-making. Thus, the integration of technology, sustainability, and human capabilities are crucial for I5.0.

# 3 Methodology

## 3.1 Data and context of study

This study presents a model that utilises I5.0 prospects to tackle future challenges in managing EOL LIBs within the automotive sector's circular economy. Through a comprehensive literature review, the paper identifies key issues in LIB remanufacturing and potential I5.0 solutions. The AHP-PROMETHEE method is employed to prioritise the development of an I5.0 supply chain for LIB remanufacturing.

To evaluate the effectiveness of Industry 5.0 prospects, five critical issues were identified through a review of the existing literature and qualitatively clustered, as presented in Table 1, along with a brief description of remanufacturing challenges. These issues served as benchmarks for assessing the impact and feasibility of I5.0 solutions in the remanufacturing context.

To ensure a robust and informed assessment, expert surveys were conducted. These surveys involved 7 specialists who possess significant expertise in I5.0, LIB remanufacturing, and relevant industrial experience. Table 1 presents a description of the experts.

The specialists were provided with a detailed questionnaire in which they evaluated and rated the identified Industry 5.0 imperatives, comparing each one against the identified challenges and assigning a score from 1 ("Not useful") to 5 ("Extremely Useful"). Table 2 summarises main prospects identified in the literature review section.

The AHP method will be utilised to assign weights to remanufacturing challenges based on expert evaluations, establishing a foundation for assessing the effectiveness of various I5.0 strategies in addressing these issues. Subsequently, the PROMETHEE approach will apply these weights to rank and evaluate different I5.0 focus areas. The outcomes of this analysis will support policymakers, carmakers, and stakeholders in prioritising I5.0 initiatives and formulating sustainable strategies for LIB remanufacturing.

## 3.2 Hybrid AHP-PROMETHEE

This article proposes a hybrid model that integrates the Analytic Hierarchy Process (AHP) and the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) to solve the multi-criteria decision-making (MCDM) problem. In this way, a panel of experts can weigh the relative importance of the selected challenges and prioritise the most suitable technologies to address them.

The AHP approach, introduced by Saaty [50], establishes a hierarchical model where pairwise comparisons determine the relative importance of criteria and alternatives, leading to overall performance scores. AHP is particularly effective for handling complex, multi-criteria decisions. It includes a consistency check for reliable criteria weighting and allows for input from diverse stakeholders. Additionally, AHP is versatile and applicable to various decision-making contexts.

The PROMETHEE method ranks and evaluates alternatives based on multiple criteria, incorporating both qualitative and quantitative factors [51, 52]. PROMETHEE is suitable for prioritising multiple alternatives and provides a complete ranking rather than just identifying the best option. It is transparent, user-friendly, and accessible for both research and practical applications. The method includes PROMETHEE I for partial ranking and PROMETHEE II for complete ranking.

In the hybrid model, the process begins with pairwise comparisons using an evaluation matrix, followed by assigning preference functions with values from 0 to 1. The global matrix aggregates these results to form a ranking [53]. The standardised nine-point scale (Saaty scale) is used in this work for pair-wise comparisons and alternative evaluations (Table 3).

The process to obtain the criteria weight by applying the AHP method and determine the ranking of alternatives through PROMETHEE is reported as follows:

1. Pairwise comparison matrix of the criteria, where $p_{ij}(i, j = 1, 2, \ldots, m)$ denotes the importance of $i$ in relation to ele-

**Table 2** List of I5.0 enablers and prospects

| Notation | I5.0 Enabler Prospect | Prospect Description | References |
|---|---|---|---|
| $A_1$ | Additive manufacturing | Precision manufacturing with minimised waste and resource optimisation | [37, 38] |
| $A_2$ | Predictive maintenance | Identifies and prevents equipment issues, optimising sustainability and efficiency | [37] |
| $A_3$ | Cognitive cyber-physical Systems | Real-time adaptation to demand changes, agility, and intelligence | [37] |
| $A_4$ | Man–Machine symbiosis | Strengthens human cognition for safer man–machine symbiosis | [42] |
| $A_5$ | Cloud manufacturing | Global collaboration and resource sharing, decentralisation, and cooperation | [37] |
| $A_6$ | Strategic unit placement | Strategic placement of manufacturing units and optimal location of plants near raw materials, and low costs | [41] |
| $A_7$ | Collaborative robots | Positive human-robot relationship, performance optimisation, and risk reduction | [37, 43] |
| $A_8$ | Blockchain technology | Decentralised trust, secure transactions, transparency, and streamlined processes | [37] |
| $A_9$ | Digital product passport | Enables secure digital identities, like product life-cycle data management | [43] |
| $A_{10}$ | Virtual and augmented reality | Improved skill development and precision in inventory management | [41, 44] |
| $A_{11}$ | Real time advisory | Enhances real-time information transfer and quality control providing flexible operations and technical advice | [14, 43] |
| $A_{12}$ | Next-gen wireless networks (5 G/6 G) | Faster, more reliable, more efficient communication, and seamless connectivity | [41, 45] |
| $A_{13}$ | Smart wearables | Improved productivity and worker safety in a human-centric environment | [42] |
| $A_{14}$ | Industrial metaverse | Bridging real and virtual worlds for interaction and influence | [46] |
| $A_{15}$ | Bio-inspired technologies | Sustainable and smart material usage, and recoverability | [39, 40] |
| $A_{16}$ | Digital twin | Online emulation tool for system redesign, reconfiguration, and optimised operation | [43] |
| $A_{17}$ | Edge computing | Offloading tasks from the cloud to IoT devices at the network edge | [47] |
| $A_{18}$ | Edge IoT | Low latency, high-quality services, extensive IoT infrastructure, and integrated AI | [48] |
| $A_{19}$ | Internet of everything | Holistic connectivity and total integration for efficient decision-making | [37, 49] |

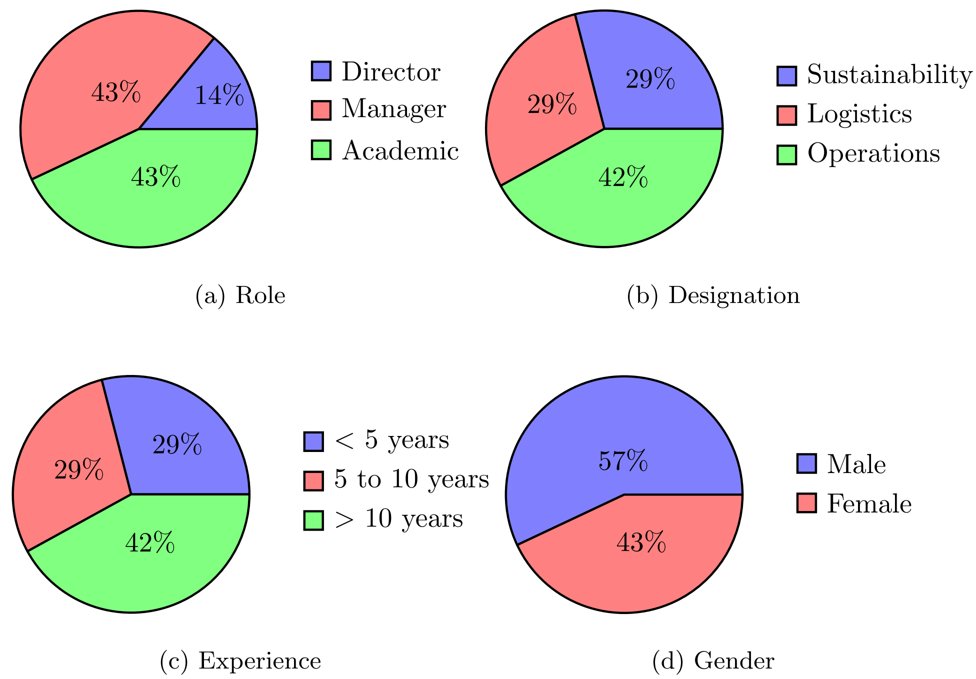


**Fig. 1** Demographic Characteristics of the 7 Evaluators. **a** illustrates the distribution of roles among the evaluators. **b** shows the distribution by designation. **c** represents the experience levels of the evaluators. **d** shows the gender distribution

**Table 3** Saaty scale for criteria evaluation

| Numerical value | Linguistic assessment |
|---|---|
| 1 | Equal importance |
| 3 | Moderate importance |
| 5 | Strong importance |
| 7 | Very strong importance |
| 9 | Very strong importance |
| 2, 4, 6, 8 | Intermediate values |

ment $j$, $o$ is the total number of criteria

$$P = \begin{bmatrix} a_{11} & \dots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mm} \end{bmatrix} p_{ij} = 1,\, p_{ji} = 1,\, p_{ij},\, p_{ji} \neq 0 \tag{1}$$

2. Obtain the element weights based on the eigenvector. To find such a vector we need to set up a matrix equation. where W is the element weights matrix, and $\lambda_{\max}$ is the eigenvalue of the matrix A.

$$PW = \lambda_{\max} W \tag{2}$$

$$(P - \lambda_{\max} I)W = 0 \tag{3}$$

3. $\lambda_{\max}$ is found by solving Eq. 4, deducted by Eq. 3, where $I$ is the identity matrix.

$$\det(P - \lambda_{\max} I) = 0 \tag{4}$$

4. Determine the consistency of the evaluations by comparing the Consistency Ratio ($CR$) in Eq. 5 with the Consistency Index ($CI$) in Eq. 6. $RI$ is the Random Index value deducted from the dimension of the matrix. The ratio must be less than 0.10 in order to consider the comparisons acceptable.

$$CR = \frac{CI}{RI} \tag{5}$$

$$CI = \frac{\lambda_{\max} - m}{m - 1} \tag{6}$$

5. The decision matrix is normalised based on the criteria using Eq. 7 for beneficial criteria and Eq. 8 for cost criteria.

$$R_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}, \quad \forall i = 1, \dots, n; \quad \forall j = 1, \dots, m \tag{7}$$

$$R_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})}, \quad \forall i = 1, \dots, n; \quad \forall j = 1, \dots, m \tag{8}$$

6. Determine the deviation based on pairwise comparison. Apply the preference function $P_j(i, i')$ to determine the preference of each alternative over the other:

$$P_j(i, i') = \begin{cases} 0 & \text{if } R_{ij} \leq R_{i'j} \\ R_{ij} - R_{i'j} & \text{if } R_{ij} > R_{i'j} \end{cases} \tag{9}$$

**Table 4** AHP results

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | CR (%) |
|---|---|---|---|---|---|---|
| Expert 1 | 6.0% | 3.9% | 30.4% | 45.3% | 14.4% | 7 |
| | (1.2%) | (1.7%) | (10.5%) | (16.5%) | (6.8%) | |
| Expert 2 | 35.1% | 14.0% | 32.0% | 12.0% | 6.9% | 3 |
| | (11.9%) | (4.4%) | (3.6%) | (1.2%) | (2.2%) | |
| Expert 3 | 13.6% | 11.6% | 28.8% | 42.0% | 4.0% | 8 |
| | (5.4%) | (5.3%) | (10.6%) | (17.3%) | (2.0%) | |
| Expert 4 | 10.4% | 5.5% | 31.5% | 46.3% | 6.3% | 4 |
| | (4.0%) | (0.6%) | (9.4%) | (13.4%) | (2.3%) | |
| Expert 5 | 32.4% | 11.2% | 31.3% | 18.4% | 6.7% | 10 |
| | (10.5%) | (6.7%) | (10.1%) | (10.2%) | (2.9%) | |
| Expert 6 | 14.3% | 8.5% | 37.3% | 28.5% | 11.4% | 7 |
| | (4.7%) | (1.2%) | (9.5%) | (14.2%) | (5.5%) | |
| Expert 7 | 31.9% | 8.8% | 35.4% | 17.1% | 6.9% | 7 |
| | (10.3%) | (4.9%) | (5.9%) | (8.1%) | (3.4%) | |
| Aggregated | 18.9% | 9.0% | 35.9% | 28.3% | 7.9% | |
| | (2.9%) | (2.1%) | (2.9%) | (4.3%) | (1.6%) | |

7. Calculate the aggregated preference function $\pi(i, i')$ considering weights assigned to each criterion, where $w_j$ is the weight of criterion $j$ calculated from AHP:

$$\pi(i, i') = \frac{\sum_{j=1}^{m} w_j \cdot P_j(i, i')}{\sum_{j=1}^{m} w_j} \tag{10}$$

8. Calculation of outranking flows/PROMETHEE I partial ranking, where n is the number of alternatives:

$$\phi^+(i) = \frac{1}{n-1} \sum_{i'=1}^{n} \pi(i', i) \qquad (i \neq i') \tag{11}$$

$$\phi^-(i) = \frac{1}{n-1} \sum_{i'=1}^{n} \pi(i, i') \qquad (i \neq i') \tag{12}$$

9. Calculate the net outranking flow/PROMETHEE II complete ranking. A higher value of $\phi^+(i)$ indicates that the alternative is better than an alternative with a lower $\phi(i)$ value.

$$\phi(i) = \phi^+(i) - \phi^-(i) \tag{13}$$

A more detailed discussion is available in recent literature [52, 53].

## 4 Results

To identify the importance of each challenge, researchers helped the respondents achieve a preference matrix with a $CR < 10\%$. Table 4 presents the final prioritisation for each respondent and the aggregated data, including the weight $w_i$ and error $e_i$ (in parentheses). The last pair of columns shows the aggregate values (the average value of the individual evaluations) for the weight and error. The last row shows the consistency of the judgements. Following AHP analysis, Table 4 reflects the critical role of each challenge identified in the literature analysis for each expert involved. Business Performance Management Singapore (BPMSG) software was used to run the calculations [54].This tool facilitated accurate calculations of weights while maintaining a CR below the acceptable threshold of 10%.

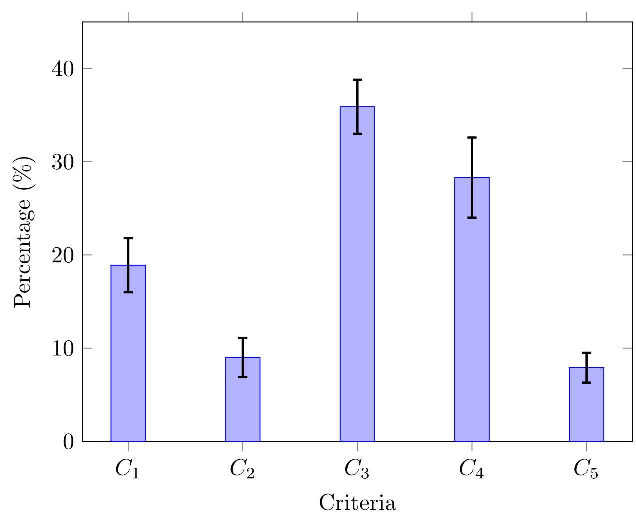


**Fig. 2** Weight distribution and intervals

Figure 2 shows the weight distribution and intervals for the weights. The AHP analysis reveals that C3 (Diagnostic and battery status tracking) has the highest weight (35.9%),

**Table 5** PROMETHEE method results: $\phi^+$, $\phi^-$, net flow, and rank

| Notation | $\phi^+$ | $\phi^-$ | Net Flow | Rank |
|---|---|---|---|---|
| A1 | 0.098642721 | 0.25520071 | −0.156557989 | 18 |
| A2 | 0.091825622 | 0.131665823 | −0.0398402 | 11 |
| A3 | 0.117670187 | 0.111159451 | 0.006510736 | 8 |
| A4 | 0.079274517 | 0.151730237 | −0.07245572 | 14 |
| A5 | 0.148599011 | 0.09233598 | 0.056263032 | 7 |
| A6 | 0.04591322 | 0.284343323 | −0.238430102 | 19 |
| A7 | 0.099616465 | 0.212927397 | −0.113310932 | 16 |
| A8 | 0.124535617 | 0.148042325 | −0.023506708 | 10 |
| A9 | 0.333177985 | 0.041670981 | 0.291507004 | 1 |
| A10 | 0.08918896 | 0.143575516 | −0.054386557 | 13 |
| A11 | 0.138340869 | 0.268571997 | −0.130231128 | 17 |
| A12 | 0.196154494 | 0.114274334 | 0.08188016 | 6 |
| A13 | 0.168913389 | 0.211854425 | −0.042941036 | 12 |
| A14 | 0.232890028 | 0.121183331 | 0.111706696 | 4 |
| A15 | 0.090702345 | 0.176398022 | −0.085695677 | 15 |
| A16 | 0.251333117 | 0.059764458 | 0.191568659 | 2 |
| A17 | 0.171283406 | 0.08135398 | 0.089929426 | 5 |
| A18 | 0.124534498 | 0.136055691 | −0.011521194 | 9 |
| A19 | 0.269048689 | 0.12953716 | 0.139511529 | 3 |

reflecting its critical role in extending battery life and optimizing the remanufacturing process. C4 (Safe and economic disassembly), at 28.3%, also holds substantial importance, emphasising the need for streamlined and safe procedures in dismantling battery components. C1 (Standardization of battery shapes and features) follows with a weight of 18.9%, underscoring the challenges of variability in battery design, while C2 and C5 have weights of 9.0% and 7.9% respectively. The weight distribution confirms the dominance of C3 and C4, with minor variations in intervals demonstrating consistency across expert judgments, respectively 2.9% and 4.3%.

The PROMETHEE method was employed to rank and evaluate various I5.0 enablers based on their ability to address remanufacturing issues. The analysis used the preference indices $phi^+$ (positive flow), $phi^-$ (negative flow), and the net flow ($\phi$), presented in Table 5. $phi^+$ index represents how much an enabler is preferred over all other alternatives based on the given criteria, while $phi^-$ reflects how much an enabler is less preferred compared to all other alternatives. The net flow is calculated as the difference between the positive and negative flows ($\phi = \phi^+ - \phi^-$). It represents the overall preference for an enabler.

From the results in Fig. 3, DPP (A9) emerged as the top-ranked enabler with the highest net flow of 0.2915. The DPP's top ranking stems from its ability to provide transparent and detailed lifecycle data, ensuring seamless tracking of battery origin, composition, and SOH. DT (A16) and IoE (A19) followed closely, with net flows of 0.1916 and 0.1395, respectively, highlighting their strong capabilities in optimising and integrating remanufacturing processes. DTs simulate real-time operational scenarios, enabling predictive maintenance and optimized remanufacturing workflows. Meanwhile, IoE integrates data from various sources, enhancing decision-making and ensuring traceability across the supply chain. Other notable enablers include IM (A14) and EC (A17), ranked fourth and fifth, demonstrating their value in bridging real and virtual environments and decentralising data processing. Next-gen Wireless Networks (A12) also performed well, securing the sixth rank due to its ability to enhance connectivity and communication efficiency. Conversely, Strategic Unit Placement (A6) and Man–Machine Symbiosis (A4) were ranked lower, with net flows of −0.2384 and −0.0725, respectively. These lower ranks suggest that, despite their potential benefits, these enablers may not be as effective in addressing the specific challenges of remanufacturing within the context of this study. AM (A1), while valuable in minimising waste, was ranked 18th with a net flow of −0.1566, indicating its relative inefficacy compared to other enablers in this specific application. The top-ranked enablers, such as DPP and DT, should be focal points for advancing sustainable and efficient remanufacturing processes for LIBs. Together, DPP, DT, and IoE create a powerful synergy that enhances transparency, facilitates predictive analytics, and integrates real-time data into remanufacturing workflows.

DPP allows for detailed tracking of a battery's usage history, facilitating the assessment of its remaining useful life and determining its suitability for remanufacturing. By iden-

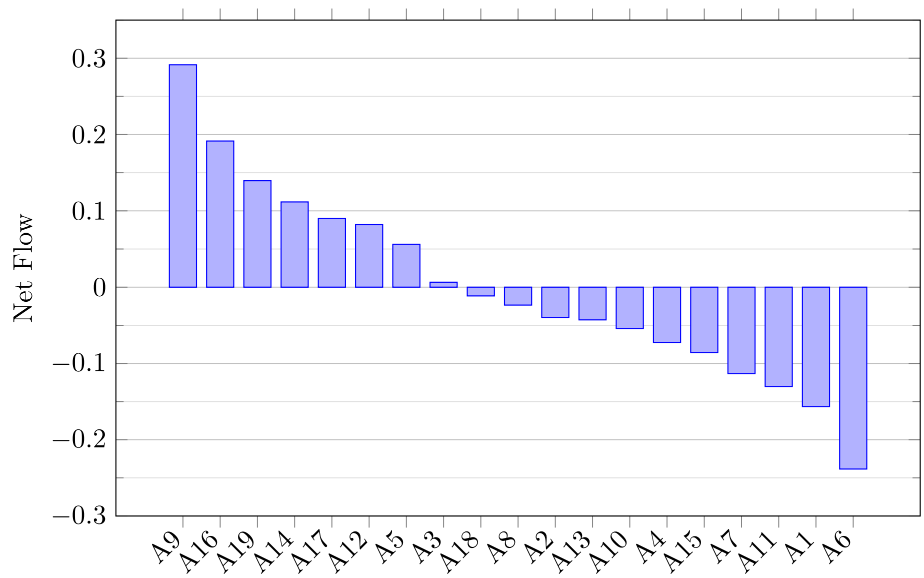


**Fig. 3** Relevance of each 5.0 prospect to remanufacturing challenges

tifying the specific components and materials used in each battery, DPP aids in the efficient disassembly and material recovery. Additionally, it ensures that remanufactured batteries meet regulatory standards by providing a detailed account of their history and compliance status. DT involves creating a virtual replica of the physical battery, allowing for real-time monitoring and simulation. Applied to LIB remanufacturing, DT can simulate various stress scenarios and predict potential failures, aiding in the early detection of issues during the remanufacturing process. By running simulations, DT identifies the most efficient methods for disassembly, material recovery, and reassembly, optimising the remanufacturing process. DT also enables continuous monitoring of remanufactured batteries, ensuring they meet quality standards and perform reliably in real-world conditions. Finally, IoE integrates people, processes, data, and things to create a connected ecosystem. In the context of LIB remanufacturing, IoE enables seamless integration of data from various sources, such as DPP and DT, creating a holistic view of the battery's lifecycle and remanufacturing process. IoE facilitates automated decision-making based on real-time data, optimising workflows and reducing human intervention. It also enhances coordination across the supply chain by providing real-time updates on inventory levels, demand forecasts, and logistics, ensuring timely availability of materials and components.

The interaction between DPP, DT, and IoE creates a powerful synergy that transforms the remanufacturing of LIBs. DPP provides detailed data on each battery, which is then fed into the DT for real-time simulation, monitoring, and process optimization. IoE ensures seamless data integration across the supply chain, enhancing traceability, transparency, and facilitating real-time adjustments based on insights from DT simulations. This collaboration enables predictive analytics, allowing potential failures to be identified and addressed proactively, thereby reducing downtime and ensuring that remanufactured batteries consistently meet regulatory standards and quality benchmarks.

In practice, the process begins with scanning each battery's DPP to retrieve its complete history. This data informs the DT, which creates a virtual model of the battery to determine the optimal disassembly method. IoE coordinates with robotic systems to execute disassembly efficiently, minimising waste and recovering valuable materials. After reassembly, the updated DPP is uploaded to the cloud, where IoE allows for continuous monitoring of the battery's performance in the field, providing valuable data for future remanufacturing cycles.

## 5 Sensitivity analysis

The study employs a two-phase sensitivity analysis to address potential uncertainties and subjectivity associated with decision-maker judgements, which can lead to inconsistencies in the ranking of alternatives. In the first phase, the analysis evaluates the impact of varying the weight of the most significant criterion on the overall ranking outcomes. Specifically, the weight of this key criterion is systematically reduced by increments of 5%, 10%, 25%, 50%, 75%, and 90%. To maintain the integrity of the overall model, the weights reduced from the primary criterion are proportionally redistributed among the other criteria, ensuring that the total weight remains equal to 1. Different weight configurations reflect the possible variability in decision-makers' preferences and priorities.

The results, presented in Fig. 4, demonstrate the top ranking alternative resilience.

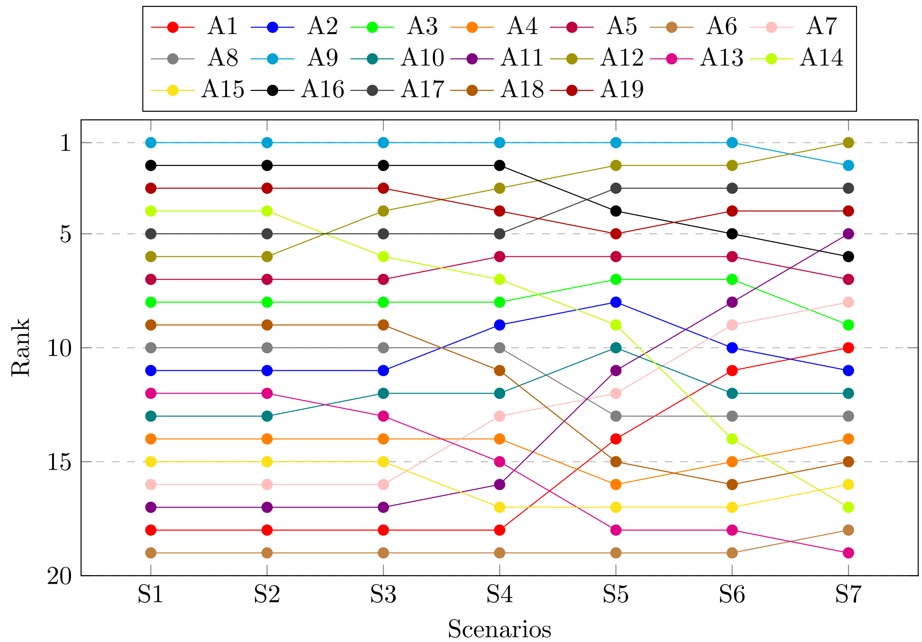


**Fig. 4** Results of using different criteria weights across scenarios

Figure 4 shows how A3, A4, A5, A6, A7, A8, and A9 exhibit stable rankings across all scenarios, suggesting a less sensitive nature compared to different criteria weights and their robustness to variations. Nonetheless, A9 consistently holds the top position across all scenarios (S1–S6), only dropping to the second position in S7, outranked by A12. When A9's weight was reduced incrementally, its ranking remained stable across most scenarios, demonstrating its resilience and strong performance across all the criteria. Conversely, A6 consistently ranks last (19) in all scenarios except S7, where it ranks 18. This stability in the bottom rank suggests that A6 is consistently the least favourable alternative, regardless of the weight distribution.

A16 consistently ranks near the top, starting at 2nd place in S1 and maintaining a strong position, eventually settling at 6th place in S7. Although it experiences a slight decline, A16 remains within the top tier. A19 maintains a stable position within the top 4 ranks across all scenarios. It starts at 3rd place in S1 and ends in 4th place in S7. A12 shows significant sensitivity to weight changes. It improves from 6th place in S1 to the top rank by S7. This significant rise indicates that A12 is highly sensitive to the redistribution of weights, particularly when less emphasis is placed on the most important criterion. Further analyses could be of interest to verify the robustness of this result, such as exploring scenarios with different weight combinations or examining how marginal changes in weights influence A12's ranking.

Secondly, a comparative analysis is performed with five other MCDM methods: Simple Additive Weight (SAW), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). Figure 5 presents the final rankings for each method.

The plot reveals clear preferences and variations in the ranking of alternatives across different MCDM methods. The consistency of rankings across MCDM methods was further validated by the Spearman Correlation Coefficients (SCC) presented in Table 6. The SCC values demonstrate strong alignment among the methods, with coefficients such as 0.989 between PROMETHEE-II and SAW, 0.977 between PROMETHEE-II and TOPSIS, and 0.925 between PROMETHEE-II and VIKOR. A9 emerges as the most reliable alternative, suggesting that these methods produced nearly identical rankings of the alternatives. This indicates a strong consensus on its superiority across methods. Moreover, A16 demonstrates strong consistency, ranking second across PROMETHEE-II, SAW, and VIKOR, and achieving a fifth position in TOPSIS. Nevertheless, A19 exhibits inconsistencies, ranking third in PROMETHEE-II, fifth in SAW, fifth in VIKOR, and eighth in TOPSIS. Despite those slight variations, A19 remains firmly positioned among the top enablers across all methods.

## 6 Discussion

Whereas the traditional linear supply chain model considers multiple entities working together in a dispersed fashion, the cooperative and synergistic approach has gradually gained traction. In order to tackle the challenges provided by a competitive and globalised market as well as the evolving expectations of customers, collaboration among numerous stakeholders has become essential. Value-chain real-time

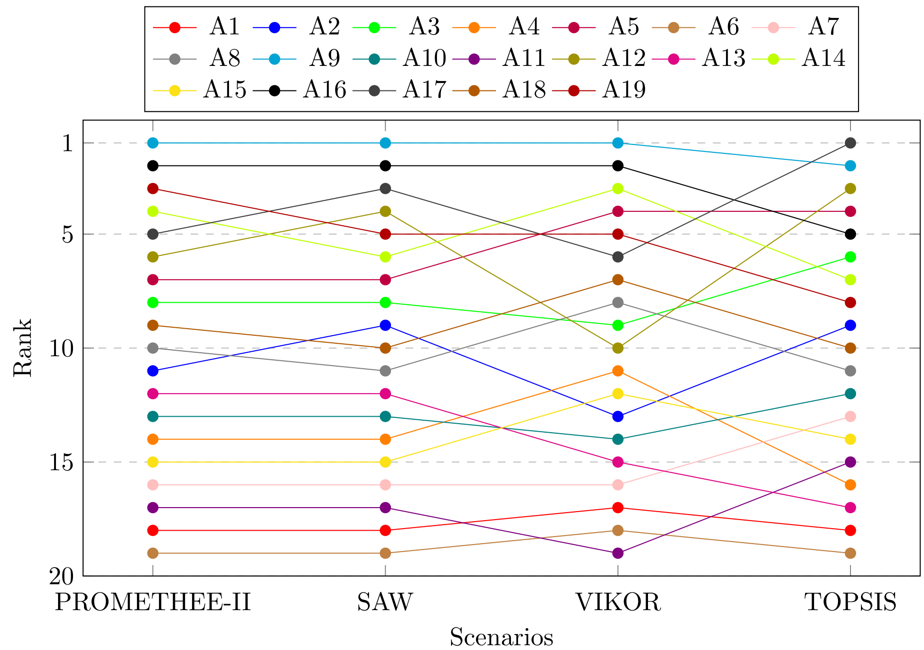


**Fig. 5** Results of different MCDM methods

**Table 6** SCC for different ranks from different MCDM methods

| | PROMETHEE-II | SAW | VIKOR | TOPSIS |
|---|---|---|---|---|
| PROMETHEE-II | 1.000 | 0.989 | 0.925 | 0.977 |
| SAW | 0.989 | 1.000 | 0.918 | 0.982 |
| VIKOR | 0.925 | 0.918 | 1.000 | 0.939 |
| TOPSIS | 0.977 | 0.982 | 0.939 | 1.000 |

data sharing is a characteristic that most integrated systems share [55]. Stakeholder's empowerment is essential to fully leverage knowledge throughout the battery lifecycle [56]. Therefore, information technology can improve supply chain visibility, coordination, and reliability [57].

At the EOL stage, Open Circuit Voltage (OCV), current, and temperature alone are insufficient for proper decisions due to Battery Management System (BMS) constraints leading to historical data losses and deficiencies [23]. There is broad agreement in the literature on the importance of automated diagnostics and rapid screening methods for battery health estimation and remanufacturing. Key data-sharing requirements include timeliness, cost, flexibility, and accuracy, aligning with low latency, low cost, flexibility, and reliability in the IoT domain [58]. So, sensors already placed in the battery system coupled with machine learning is the most cost-effective and studied method for sorting EOL batteries [20]. Data-driven approaches are extensively studied to enable RUL prediction by identifying the appropriate input features [17]. The highest-weighted criterion, C3, highlights the necessity of advanced diagnostic methods for evaluating the SOH and RUL of LIBs. Improving diagnostic accuracy, particularly through data-driven approaches, is pivotal in extending battery lifecycle and reducing waste. From a remanufacturing perspective, it is crucial to determine the optimal time to establish the EOL of the battery. Identifying the optimal remanufacture time can prevent severe battery deterioration [59]. However, historical information (manufacturer, model, production date, battery type, operation history, retirement reasons) is crucial to determining the salvage value and deciding on remanufacturing [17]. Standardised battery labelling reduces sorting, testing times, and costs related to dismantling battery packs and modules [60]. Tracking dimensions like materials chemistry, origin, and condition is also effective [61]. Circular capabilities require a comprehensive perspective on the product life cycle. Consequently, a digital product identity emerges from this need [62]. A battery passport with manufacturing and disassembly details facilitates automation and material pre-identification [63, 64]. The DPP is a digital identity associated with products or batches. A unique identity, product data and instructions, maintenance and disassembly directions, carbon footprint, recycling history, and certificates can be stored in the DPP [65]. New European regulations recently mandate DPPs use for new batteries, referred to as Digital Battery Passports (DBPs), in order to improve management and circularity [66]. Disposal phase could benefit from data inside the DBP to identify critical materials, steer EOL management decisions, and optimise remanufacturing. As the electric vehicle market grows, sustainable battery management becomes increasingly vital.

The proposal for "Ecodesign for Sustainable Products Regulation" (ESPR) conceptualises the Digital Product Passport (DPP). Here, the EU asks for tracking a product's information along its lifecycle [67, 68]. The ESPR definition is as follows:

> A set of data specific to a product that includes the information specified in the applicable delegated act adopted pursuant to Article 4 and that is accessible via electronic means through a data carrier in accordance with Chapter III.

A DPP is a tool for tracking down product or asset information, giving various stakeholders access to comprehensive information about the product's origin, composition, repair, and disassembly options [69].

Academics see as strategic the introduction of DPP to create new value across battery supply chains. DPP can help industry actors find better solutions for reducing emissions and carbon footprint, boosting new business models and resource efficiency. Initially, implementing this tool in the battery value chain can address transparency challenges and offer insights for applying similar requirements to other products. Access to RUL and SOH information can significantly enhance recovery effectiveness. Publicly available battery information (i.e., carbon footprint data) can empower final consumers and promote environmental-driven decisions for multiple stakeholders [70]. Product lifecycle data encourages innovation and helps retailers find new ways to better customise goods for the end user [69]. Full transparency of life cycle data allows informed decisions and scaling of new business models [62]. Validation of sourcing and responsible processes across the value chain can reward companies with ambitious sustainability practices integrating proactive due diligence and ensuring adherence to responsible sourcing standards.

Sharing battery in-use data is perceived as a competitive disadvantage and raises concerns about intellectual property rights [71]. Initially, OEMs need access to key life cycle inventory data in order to analyse battery impacts and make sustainability sound choices. For the purpose of maintenance and allowing second life applications, the following firms that handle EOL batteries require data on the battery's SOH. Data sensitivity and intellectual property hinder data sharing, and processing and storage infrastructure must be carefully designed for massive amounts of data that are now in use. Battery chemistry, material composition, and disassembly instructions are crucial for disassembly and subsequent operations. Intellectual property concerns and a lack of incentives for data sharing thus hinder the spread of information [72]. Manufacturers are the main producers of new information since they create and alter new products. An increase in data demand may result in additional expenses. Thus, IoT, blockchain, and other digitalisation technologies can improve efficiency in data collection and security [69].

Transparency is currently stressed by the DPP ecosystem, although this could result in risks of excessive data acquisition and needless data collecting. Rather than developing new standards, DPP should include existing ones. Consequently, making use of prior knowledge and established criteria [73].

In 2024, the EU Sustainable Batteries Regulation established EOL management, sustainability, safety, and labelling requirements for batteries. It also introduces the DBP, a digital record system retrievable through a QR code that serves as a unique product identifier for industrial and mobility batteries exceeding 2 kWh [74]. The QR code is required to be associated to a unique identifier set by the economic operator, responsible for battery commercialisation. When a battery is considered waste, the responsibilities of the battery passport transfer to the producer or waste management operator This system requires data to be collected from a variety of actors, including manufacturers of cell and module assemblies, battery manufacturers, automotive OEM, and businesses that provide battery service, refurbishment, and repurposing. Concurrently, Multiple stakeholders will have access to battery related information (e.g., manufacturer, battery category, capacity, and hazardous and critical materials). Even carbon footprint will be disclosed coupled with responsible sourcing, recycled content, and the share of renewables.

From 2024 on, battery management systems must include parameters for determining the SOH and expected lifetime of batteries. From 2025 on, carbon footprint declarations (labels) are required, and symbols for separate collection included on labels. Economic operators must fulfill due diligence obligations, adopting and communicating policies on raw materials and social and environmental risks, along with establishing systems for controls and supply chain transparency. Moreover, take-back and collection systems and ensure waste EVBs are delivered to treatment facilities must be designed by manufacturers, while recyclers must meet minimum recycling efficiency targets for various battery types. In this field several areas of research has been identified and explored.

Regulatory structures and technical standards in the second-life battery industry are explored by [66, 75] presents a first DBP concept for BEVs, considering 54 data points under four main categories: battery, sustainability and circularity, diagnostics, maintenance and performance, and value chain actors. The incorporation of LCA into DBPs is covered by [76]. Stakeholder needs for using secondary data, data sharing options, and LCA stages in DBPs are classified. In order to enable LCA and EU compliance, [77] presents a

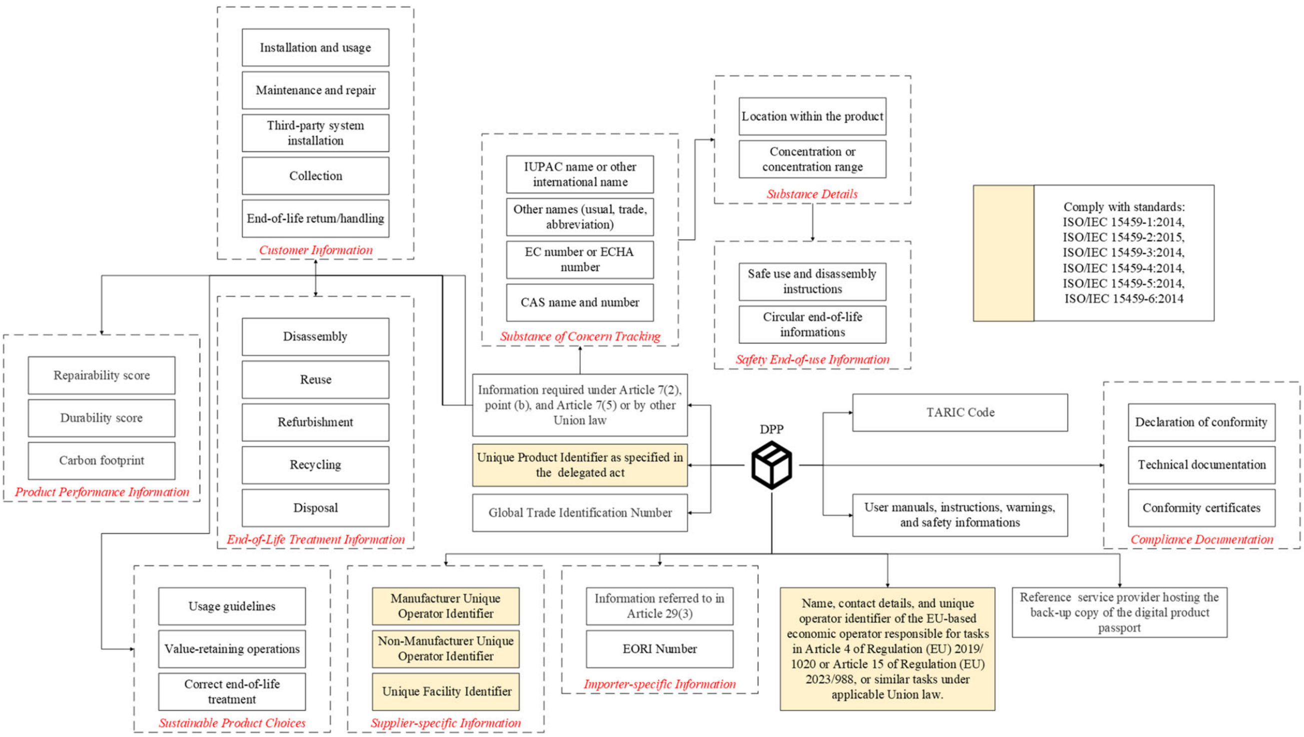


**Fig. 6** Schematic of DPP possible contents in ESPR [68]

standardised DBP data format for lifecycle monitoring and data exchange.

In 2026, carbon footprint performance class requirements will come into effect, and general information labels will be required. The DBP will be established and fully interoperable with other DPPs by 2027 and a maximum carbon footprint threshold will be implemented by 2028. Recyclers must meet new efficiency targets for lead-acid (80% by average weight) and lithium-based batteries (70% by average weight), while minimum shares of recovered materials in batteries will be mandated, and further recovery targets will be set for recyclers by 2031. Finally, by 2036, the required minimum shares of recovered materials will further increase.

The implementation of DPPs faces several weaknesses and threats that must be addressed to enable successful adoption. The lack of uniform standards across industries and regions presents challenges for achieving interoperability, while risks associated with managing sensitive data, including proprietary and personal information, raise concerns about security and compliance. Furthermore, the absence of a clear updating procedure throughout a product's life cycle complicates long-term management and usability. These issues are compounded by external threats, such as evolving regulations that introduce additional complexities, and reliance on digital infrastructure, which increases vulnerability to failures and cyberattacks. Consumer concerns about data privacy and security also pose significant hurdles, potentially resulting in resistance and backlash against the technology. Overcoming these challenges requires the development of a robust framework to enhance data security, standardise practices, and ensure regulatory compliance.

[78] study traceability systems in battery cell production to enhance product quality and minimise scrap. The study proposes a product-specific identifier, linking continuous and discrete production steps. [79] identifies DPP system requirements, focusing on stakeholder involvement and existing literature. The study categorizes these requirements to highlight gaps in current DPP systems, emphasizing the need for a robust digital infrastructure to support the creation and management of DBPs.

[80] explores the data needs and requirements of EVB value chain actors for sustainable battery management. The study reveals varying perspectives on data needs and availability, attributing these differences to the actors' roles in the value chain and the lack of well-defined information flows. The research provides insights into the information content required for effective DBPs. [81] introduces a DBP system leveraging Ultra-High-Frequency (UHF) RFID technology to enhance battery traceability, reduce waste, and increase resource efficiency. The study provides a proof of concept and discusses the potential benefits of such a system for sustainable energy management.

[71] and [75] both underscore the potential of DBPs to support sustainable and circular battery management. By

providing high-quality data, DBPs can facilitate the reuse, repurposing, and recycling of batteries, extending their lifecycle and reducing environmental impacts.

## 7 Conclusion

This paper explored the potential of I5.0 technologies to optimise the remanufacturing of LIBs within the context of the circular economy. The study identified key challenges in the LIB remanufacturing process and employed a hybrid AHP and PROMETHEE approach to prioritise I5.0 enablers that can address these challenges effectively. The results highlighted the DPP, DT, and the IoE as the most impactful technologies, offering significant potential to improve the efficiency, sustainability, and traceability of the remanufacturing process. These technologies work together to provide comprehensive data management, real-time monitoring, and seamless integration across the supply chain, ensuring that remanufactured batteries meet regulatory standards and perform reliably.

The study demonstrated the robustness of the proposed model through a sensitivity analysis, revealing that top-ranked I5.0 enablers consistently perform well across different weight configurations. The comparative analysis using multiple MCDM methods further validated the reliability of the top-ranked alternatives.

In addition to identifying the most promising I5.0 enablers, this research also contributes to the understanding of how DBPs can transform the remanufacturing process. The study highlights the critical role of data-driven approaches in improving decision-making, optimising workflows, and enhancing the overall efficiency of the remanufacturing process. The integration of sensors and machine learning technologies provides cost-effective solutions for sorting EOL batteries and predicting RUL. The introduction of DBPs enables comprehensive tracking of a battery's lifecycle, from manufacturing to disposal, improving transparency, recycling, and resource efficiency. Therefore, LIB remanufacturing can achieve low material consumption and waste through information sharing and extended OEM responsibility. However, the implementation of DBPs faces challenges, including intellectual property concerns, data sensitivity, and the need for robust digital infrastructure. Stakeholder collaboration and regulatory support will be crucial in overcoming these barriers.

Future work could explore the practical implementation of these I5.0 technologies in real-world remanufacturing settings, focusing on the integration of DPP, DT, and IoE within existing supply chains and barriers. Further research could also investigate the development of new business models that leverage these technologies to create additional value in the LIB remanufacturing industry. Lastly, future studies could consider the evolving regulatory landscape, such as the EU's mandated implementation of DBPs, and how these regulations will impact the adoption and effectiveness of I5.0 technologies in the remanufacturing sector.

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**Data availability** Data will be made available on request

## Declarations

**Conflict of interest** The authors have no Conflict of interest to declare that are relevant to the content of this article.



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