THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Leveraging supplier material data to inform LCA modelling and resource assessment in the automotive industry

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ABSTRACT

This thesis investigates the application of supplier material composition data from the automotive industry's International Material Data System (IMDS) to inform sustainability assessments. A method is developed to systematically extract and process IMDS data for use in life cycle assessment (LCA) modelling. The implications of using IMDS data at varying levels of aggregation and completeness on the accuracy of LCA results are quantitatively evaluated through an LCA case study on an automotive engine. Compared to a highly detailed reference model, simplified modelling options reduced workload but compromised accuracy, especially for impacts related to resource use. A material mass cut-off of one percent of weight maintained reasonable precision while significantly decreasing effort. Decreasing the number of substances representing each material largely affected scores for most impact categories except a few, including the climate change category. Excluding manufacturing data notably impacted greenhouse gas emissions.

Additionally, this thesis performs an in-depth compositional analysis focusing on metals present in two vehicle “gliders” (the car excluding the powertrain) with distinct equipment levels. Over 50 metals are documented, and their contributions to short and long-term metal scarcity are examined. Gold, copper, bismuth, lead, molybdenum, and certain rare-earth metals face substantial supply risks. The analysis of metals across the gliders subsystems and components indicates that equipment levels significantly affect short-term supply risks for some metals. Entropy analysis is used to gather insights into the effectiveness of different substitution and secondary metal recovery strategies revealing significant challenges for the recovery and substitution of certain metals like copper and rare earths.

Overall, this thesis demonstrates the potential of leveraging IMDS data to expedite sustainability assessments in the automotive industry. However, balancing model complexity and precision remains essential. The extensive reliance of vehicles on diverse metals, even excluding the powertrain, highlights the sector's substantial resource dependence. This underscores the need for sustainable metal management in automotive manufacturing.

Keywords: International Material Data System (IMDS), life cycle assessment (LCA), life cycle inventory (LCI), vehicle gliders, metal scarcity, metal availability, automotive industry.

To all the humiliated and offended

Exploited and oppressed

Who tried to find a solution

…

Memory of a time

Where to fight for your rights

Was a defect that kills

…

But when the sun rises

I want to see who will remember

And when dawn comes

I don't want to forget

This legion that sacrificed for a new day

I want to sing this calloused hand

That brought us so much joy.

…Let's keep going on!

"Pequena Memória para um Tempo sem Memória"
Luiz Gonzaga Jr.

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And to my family, my bedrock of strength and love: Emmie, Lucas, and Theo. You always remind me of what is truly important in life! Allan, thanks for the ongoing support and for keeping me updated on the automotive world. To my parents, you are the pillars on which I stand, and I am deeply grateful for the values you have taught me.

LIST OF APPENDED PAPERS

Paper I
Bitencourt de Oliveira, F., Nordelöf, A., Sandén, B. A., Widerberg, A., Tillman, A-M., 2022. Exploring automotive supplier data in life cycle assessment – Precision versus workload. *Transportation Research Part D: Transport and Environment*, vol. 105, April 2022. https://doi.org/10.1016/j.trd.2022.103247

Paper II
Bitencourt de Oliveira, F., Nordelöf, A., Bernander, M., Sandén, B. A., 2023. Assessing metal use and scarcity impacts of vehicle gliders. *Manuscript under review*.

Table of Contents

1 Introduction

The automotive industry is confronted with significant environmental challenges, particularly in reducing carbon dioxide emissions and effectively managing the utilization of critical and scarce materials in vehicles. These challenges have far-reaching implications throughout the entire life cycle of vehicles, spanning from material extraction from Earth’s crust to end-of-life treatment.

Typically, driving-related exhaust emissions from vehicles with conventional combustion engines account for approximately 70% of their overall impact on climate change (Bieker, 2021). Car manufacturers have thus prioritized the reduction of carbon dioxide emissions, along with other pollutants, by improving drivetrain efficiency, minimizing parasitic losses, and implementing weight-saving measures to reduce fuel consumption.

To further reduce greenhouse gas emissions, extensive technological advancements are being pursued, with the goal of establishing electric power-driven vehicle fleets. This transformation aligns with other ongoing trends in the automotive industry, including the widespread adoption of lightweight materials and the increased incorporation of electrical and electronic equipment (EEE) in cars, prompted by evolving requirements for safety, comfort, digital connectivity, and automation (European Commission, 2022; Trovão, 2022).

These concurrent trends have the potential to reshape the environmental landscape of the automotive sector. While electrification holds significant promise for reducing environmental impacts during the vehicle use phase, there is a corresponding shift of such impacts to other life cycle phases (Nordelöf, et al., 2014). Furthermore, the increasing reliance on critical and scarce materials, such as rare-earth metals (REMs), cobalt, lithium, among others, presents additional challenges (Söderman Ljunggren, et al., 2013). Beyond the environmental and social concerns associated with these materials, their strategic importance within the automotive industry is underscored by the high likelihood of supply disruption and limited viable alternatives (Field III, et al., 2017; European Commission, 2020a). Consequently, the increased utilization of scarce metals in vehicles not only amplifies environmental impacts in the upstream supply chain, such as mining and extraction, but also heightens supply risks for the automotive industry itself and other industrial sectors reliant on these materials.

Addressing these environmental challenges effectively necessitates a comprehensive understanding of the material composition of vehicles, emphasizing the importance of robust and specific data on vehicle material composition. Traditionally, the automotive industry has relied on what are known as "internal databases" to gather this data, which are derived from technical drawings and component lists, and are the result of close collaboration between engineers within the company and component suppliers (Schweimer & Levin, 2000; Finkbeiner, et al., 2006; Koffler, et al., 2008). Vehicle teardown and disassembly guides have also served as methods for inventorying material data (Keoleian, et al., 1998; Danilecki, et al., 2016).

However, as these approaches are time-consuming and difficult to replicate across multiple cars and models, more recently the industry has turned to the International Material Data System (IMDS). This web-based, industry-wide database, collaboratively developed by automotive manufacturers, houses data on all components and their material content present in finished vehicles, provided by over 150,000 registered suppliers (DXC Technology, 2017). The main goal of the IMDS is to assist manufacturers and their suppliers in meeting the obligations set by standards, laws, and regulations. With detailed material compositions of vehicle components available in a single database, the use of IMDS in environmental studies can significantly reduce the workload required for data inventorying, compared to using a patchwork of internal data sources or conducting teardowns (Koffler, et al., 2008; Yu & Kim, 2013).

However, the utilization of material composition data from IMDS in environmental studies is not a straightforward task. Harnessing this information necessitates a series of steps to transform it into usable data. Consequently, a central aim of this thesis is to develop a method for extracting vehicle material composition data using IMDS and to explore how IMDS could expedite data inventorying in environmental studies within the automotive industry.

1.1 IMDS data and life cycle assessment: opportunities and challenges

There are different tools and methods used to assess the impacts of human action on the natural environment. Among them, life cycle assessment (LCA) is used to assess the impacts of goods and services from a life cycle perspective, by quantifying the environmentally relevant flows between the technosphere and the environment. It has been utilized by the automotive industry for over two decades mainly on the identification of environmental hotspots and to assist in prioritizing areas for product innovation (Kaniut, et al., 1997; Sullivan, et al., 1998; Warsen, et al., 2013). However, applying LCA on complex products poses a challenge due to its comprehensive nature. Vehicles, for example, composed of thousands of components, necessitate a large amount of data for the compilation of the life cycle inventory (LCI), making LCA studies both costly and time-consuming (Koffler, et al., 2008; Yu & Kim, 2013).

To streamline this process, some procedures have been developed that utilize IMDS data to expedite LCI modelling of complete vehicles (ibid.). This approach has significantly reduced the time and effort required for inventory modelling. These streamlined models use IMDS information to identify the most suitable background inventory data available in internal, openly published, or commercial LCA-databases to represent the material composition of the components.

Real-world experiences from Volvo Car Corporation (hereinafter Volvo Cars) demonstrate that such streamlining approaches have indeed expedited the execution of LCA studies for various purposes, including carbon footprint assessment. This has helped establish LCA as a standard tool within the company. However, from our practical observations, specific material datasets are often not readily available in commercial LCA databases like Ecoinvent (Wernet, et al., 2016) or Sphera (Kupfer, et al., 2021). Instead, generic LCI data for broad material categories must be employed.

It is essential to highlight that IMDS provides a level of detail that allows for more intricate LCI modelling. IMDS contains specific information on the substances present in every material, enabling LCA to be used as a tool for in-depth analysis of iterative design improvement and internal work on component requirements, in line with IMDS Terms of Use (DXC Technology, 2022). Materials and their constituent substances can be modelled with varying degrees of accuracy. In some instances, the LCI model may need to be supplemented with data that cannot be entirely derived from IMDS.

While the advantages and challenges of using IMDS data in LCA studies have been examined in previous research (Koffler, et al., 2008; Yu & Kim, 2013), the field still lacks quantitative assessments of the influence of IMDS on LCA outcomes. IMDS data can be employed and classified with differing levels of aggregation, completeness, and accuracy, and may require supplementation with data not available within the IMDS itself. Given that enhancing the level of detail in the modelling and including supplementary data demands additional work hours, it becomes crucial to understand how various approaches to utilizing IMDS data influence the exactness of LCA findings. Hence, there is a need for an evaluation of the trade-off between the effort put into modelling when employing IMDS data at different levels of aggregation and completeness, and the precision of the LCA outcomes.

1.2 Metal demand in the automotive industry

Transitioning from the discussion on the importance of detailed understanding the use of IMDS material data in LCA studies, we delve into the specifics of one such category of materials – namely metals. The automotive industry is a significant consumer of natural resources globally (Field III, et al., 2017; Ortego, et al., 2020). Beyond the usage of "industrially mature" base metals such as iron, aluminium, and copper, modern vehicles incorporate a diverse array of scarce, rare, and minor metals. These are present in a multitude of components, contributing to passenger safety and an improved driving experience.

The extensive diversity of metals found in vehicles, coupled with the high-volume production of passenger cars – over 80 million units annually – places considerable stress on the global demand for these resources (Drive Sustainability, 2018; Öko-Institut, 2018; OICA, 2021). As such, various metals integral to modern cars have been deemed strategic or even critical to the automotive industry, prompting a rising interest in identifying metals of concern within the sector.

This interest is particularly crucial from the perspective of automotive manufacturers who need to understand, for strategic reasons, the spectrum of metals used in cars, their quantities, and their distribution across different parts and components. Indeed, recent years have seen a significant expansion in the portfolio of metals used by the automotive industry, largely driven by increasingly stringent safety and environmental regulations (Lewis, et al., 2019; Restrepo, et al., 2019; European Commission, 2022; Trovão, 2022).

For example, in response to lightweighting strategies, aluminium alloys have become prominent substitutes for iron in components like engine blocks, wheels, and body-in-white (Arowosola & Gaustad, 2019; Lewis, et al., 2019). Several minor metals, such as niobium, molybdenum, and vanadium, are integrated as alloying elements in advanced high-strength steels (Theyssier, 2015). The industry's move towards electric powertrains has notably increased the demand for metals like lithium, cobalt, nickel, and various REMs (Pehlken, et al., 2017; Lee, et al., 2020). This trend is also mirrored in the increased use of palladium, tantalum, silver, and gold in a variety of electrical and electronic equipment (EEE), driven by evolving requirements for safety, comfort, digital connectivity, and automation in cars (PwC, 2013; Restrepo, et al., 2017; Nguyen, et al., 2020; Trovão, 2022).

Recent studies focusing on scarce metals in passenger cars often emphasizes comparisons between traditional internal combustion engine (ICE) vehicles and their electrified counterparts. These studies, often utilizing vulnerability assessments and exergy analysis, underscore that the shift towards electric powertrains – given the material demands of traction batteries and electric motors – stands as a principal driver of amplified demand for potentially scarce metals in the automotive sector (Ortego, et al., 2018; Knobloch, et al., 2018; Iglesias-Émbil, et al., 2020; Bhuwalka, et al., 2021).

While the push for electrification is undeniably prominent, it is vital to remember that other factors, such as lightweighting and the proliferation of EEE in cars, are also important in driving the heightened demand for several scarce, rare, and minor metals in modern vehicles. These, risk being overshadowed by the current focus on electrification. Therefore, there is a need to investigate how the metal demand in the automotive industry is influenced by these other ongoing trends. In this thesis, this gap is filled by assessing the content of metals and metalloids in two vehicle “gliders”, i.e., all the subsystems of the vehicle except the propulsion system. By excluding the most frequently investigated parts of today’s vehicles from the study and assessing two gliders with different equipment levels, we aim to pinpoint a demand for automotive metals that otherwise often gets overlooked.

2 Research questions

To address the research gaps discussed earlier, the following research questions (RQs) were formulated:

RQ1: *How can a method be developed to extract material data from the IMDS that also facilitates expedited data inventorying in environmental studies within the automotive industry?*

RQ1 was formulated to address a central aim of this thesis – to develop a method that not only extracts material composition data from the IMDS but also streamlines the process of data inventorying for environmental studies in the automotive industry. This question is addressed in Paper I and it serves as a central methodological investigation for both papers, providing a foundation for the subsequent analyses.

Transitioning from the methodological aspects to the practical application of the data obtained, we formulated RQ2.

RQ2: *How do the level of data aggregation and degree of completeness of an LCI model employing IMDS data affect the precision of environmental impact assessment results and the effort necessary to develop such models?*

RQ2 was formulated to investigate the implications of data granularity and model completeness on the accuracy of life cycle impact assessments. This question is also addressed in Paper I, where we analyse the trade-offs between precision and the effort required to build comprehensive LCI models using IMDS data.

Having established a method for data extraction and explored the effects of data aggregation and model completeness in LCA results, we then sought to delve deeper into the specific aspects of resource use and potential scarcity in Paper II by analysing two vehicle gliders with different equipment levels. Thus, we formulated the following research questions:

RQ3: *What is the metal composition of vehicle gliders and how does it differ between different equipment levels?*

RQ4: *How do vehicle gliders contribute to short and long-term potential primary metal scarcity?*

RQ5: *How does the distribution of metals across subsystems and components in gliders influence the relative complexity of substitution and secondary metal recovery?*

RQ3-5 were formulated to explore resource use in the automotive industry, focusing on the metal composition of vehicle gliders, their contribution to metal scarcity, and the potential for metal substitution and recovery. These questions are addressed in Paper II, where we apply the method developed in Paper I to perform a detailed analysis of metal usage in vehicle manufacturing.

In summary, the research questions formulated for this study are designed to address both methodological and practical aspects of using IMDS data for environmental studies in the automotive industry. The findings from these investigations provide important insights for improving current sustainability practices in the sector.

3 Methodology

This section provides detailed explanations of the methodologies employed in Paper I and II. A shared methodological approach in both papers is the use of the IMDS to extract material composition data. This extraction process forms a pivotal part of both papers, supplying critical data for the investigation and evaluation of material and environmental impacts. Due to its significant role in both studies, this process is delineated separately in Section 3.1, despite being an approach originally developed for Paper I.

Section 3.2 delves into the application of IMDS data at varying degrees of aggregation and completeness, which forms the basis of an LCA study on a vehicle combustion engine in Paper I. In Section 3.3, the methodology of Paper II is described. While this paper utilizes the same methodological approach as Paper I to extract material composition data from IMDS, the subsequent analysis of that data diverges. The focus here shifts from the influence of data completeness and aggregation on LCA results to a more comprehensive exploration of the material composition of vehicles and its potential implications for metal scarcity.

3.1 Extracting vehicle material composition data from IMDS

It comes as no surprise that the IMDS serves as a comprehensive repository of data for material composition of vehicles. This database houses information on materials and substances embedded in all individual components present in each vehicle manufactured at Volvo Cars, ranging from small items like screws to larger components such as oil pumps. Despite not being originally intended for environmental studies, the IMDS presents a wealth of data that can be harnessed for such investigations, given the appropriate methodological approach.

Extracting material composition data from the IMDS requires a sequence of steps before useful information can be produced. Figure 1 shows the overall structure of these steps employed in this thesis.

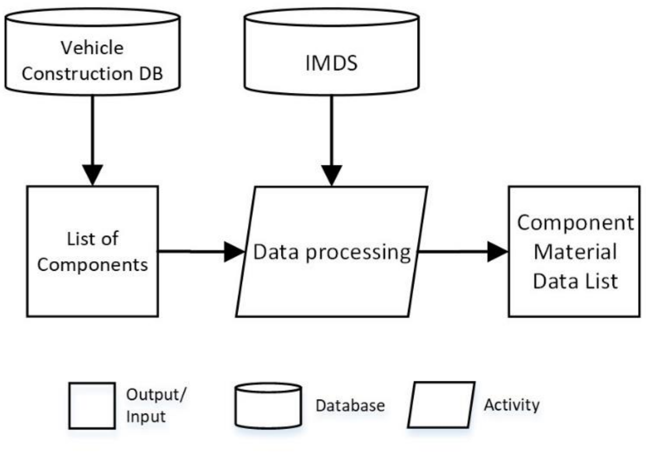

Figure 1. Overview of the steps employed in this study to extract material composition data from the IMDS.

The first step involves the creation of the list of components, which is obtained from Volvo Cars' Vehicle Construction Database. This internal database provides information for each individual component of a vehicle, including its name, identification number, quantity present in the vehicle, mass, and the *function group* to which it is associated. At Volvo Cars, the organization of components into broader assemblies and subsystems is delineated using these function group levels. These levels facilitate a hierarchically structured representation of the entire vehicle and its distinct parts, thereby providing a detailed, organized map of the vehicle's composition. Table 1 provides an illustrative example of this structure for a complete vehicle.

Table 1. A vehicle is composed of several parts, all providing specific functions. Each part can be described at several levels of aggregation, known as function group levels. E.g., function group 2000 represents the complete engine at level 1. It is composed of sub-parts reported at level 2, by function groups 2100-2800. Function groups 2110-2890 report component groups at level 3, and there is also a fourth level for single components, specified by the fourth digit (2XXX).

<table>
<tr><th colspan="5">Function group level of aggregation</th></tr>
<tr><td rowspan="13">Complete vehicle</td><td>Level 1 –
Complete part</td><td>Level 2 –
Sub-parts</td><td>Level 3 –
Component groups</td><td>Level 4 –
Components</td></tr>
<tr><td rowspan="7">2000 – Engine complete</td><td rowspan="3">2100 – Engine (block)</td><td>2110 – Cylinder head</td><td>e.g., 2116 – Gasket</td></tr>
<tr><td>2120 – Cylinder block</td><td>e.g., 2125 – Flywheel</td></tr>
<tr><td>21x0 – …</td><td>21xx – …</td></tr>
<tr><td>2x00 – …</td><td>2xx0 – …</td><td>2xxx – …</td></tr>
<tr><td rowspan="3">2800 – Ignition system</td><td>2810 – Ignition coil</td><td>e.g., 2813 – Spark plug</td></tr>
<tr><td>28x0 – …</td><td>28xx – …</td></tr>
<tr><td>2890 – Miscellaneous</td><td>e.g., 2899 – Other</td></tr>
<tr><td rowspan="2">x000 – …</td><td>x100 – …</td><td>x1x0 – …</td><td>x1xx – …</td></tr>
<tr><td>xx00 – …</td><td>xxx0 – …</td><td>xxxx – …</td></tr>
<tr><td rowspan="3">8000 – Body, interior and exterior</td><td rowspan="2">8100 – Body framework</td><td>8110 – Floor / Wheel housing</td><td>e.g., 8113 – Floor, rear</td></tr>
<tr><td>81x0 – …</td><td>81xx – …</td></tr>
<tr><td>8x00 – …</td><td>8xx0 – …</td><td>8xxx – …</td></tr>
</table>

However, since the list of components does not inherently contain material composition information, the next step involves adding this data for all components. This is achieved via an automated process where an algorithm exports material composition data stored in the IMDS for each component. This process generates what we call the component material data list, which is essentially the list of components supplemented with material composition information.

Figure 2 describes the structure of the component material data list. Materials, as per the IMDS, are physical items characterized by a homogeneous structure – no layers or visible differentiation are perceptible (e.g., steel, thermoplastic), and can be made up of multiple basic substances. These substances may be a chemical element (e.g., iron, copper), a standard compound (e.g., acrylic resin, iron oxide, glass fibre), or in cases where confidentiality is required, a wildcard (e.g., “miscellaneous, not to be declared”). The IMDS also utilizes the VDA material classification system (Verband der Automobilindustrie, 1997), which groups material entries into broad categories based on a combination of their content, properties, and applications.[1]

[1] The “VDA material classification system” was developed by the German Association of the Automotive Industry (Verband der Automobilindustrie). It was designed to categorize materials in an easily understandable structure, and its application is mandatory for all material entries in the IMDS.

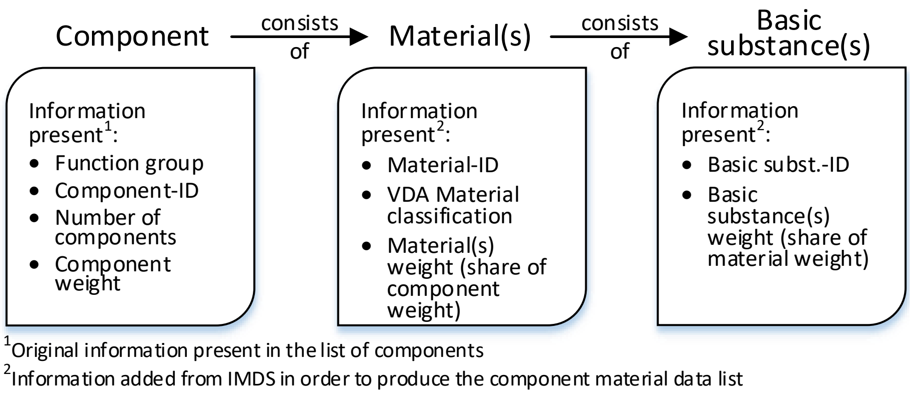

Figure 2. Structure of the component material data list and information present for every component entry in the list.

In this manner, the IMDS serves as a key tool in the extraction and utilization of material composition data, enabling a detailed investigation into the environmental impacts of various components in the automotive industry. The methodologies established in Paper I and II, centred on this use of the IMDS, lay the groundwork for the broader investigation undertaken in this thesis.

3.2 Assessing impact of IMDS data on LCA results

In Paper I, our goal was to examine how various uses of IMDS data impact the precision of LCA results. To achieve this, we conducted an LCA of a vehicle component using material composition data drawn from IMDS. We strategically chose an internal combustion engine as the subject of our assessment to constrain the volume of data needed for the modelling process. As an item composed of both bulk materials and an array of smaller components, an engine exemplifies much of the variability inherent in a complete vehicle while avoiding excessive complexity.

Our study was designed around eight modelling options, one serving as a reference model with an aspiration for a high level of detail, and seven others featuring simplified degrees of data aggregation and completeness. We evaluated the level of aggregation in each model by compiling IMDS data for the engine as either a "black box" (without differentiation between components or sub-parts) or by compiling it for distinct engine sub-parts such as the cylinder block, lubrication system, etc. Data completeness was assessed by the variation of three parameters: 1) altering the number of materials representing the engine and its sub-parts by using IMDS data with or without a mass cut-off; 2) varying the number of substances representing each material; and 3) incorporating data outside the scope of IMDS, such as component manufacturing.

The functional unit of the study was defined as one manufactured unit of the engine at the "factory gate". Our assessment in Paper I focuses on the production phase of the engine, encompassing raw material extraction, material transformation, and assembly, while excluding the utilization and disposal phases. The type of LCA performed was attributional, meaning that we modelled the impacts of producing the engine as a fraction of the impacts of the current or recent historical production system. Consequently, our study relied on average data and resolved allocation problems in multi-input or output processes by partitioning. Foreground system data, which includes the material composition and assembly of the engine, was compiled internally at Volvo Cars for all options, using data from IMDS and other complementary sources detailed in Paper I.

The data representing background systems, like upstream material extraction and manufacturing, electricity generation, and transport, was primarily sourced from the Ecoinvent database (Wernet, et al., 2016) version 3.7.1, which represents global or regional average supply (process inputs in general) or national supply (electricity). Additional data was obtained from the GaBi professional database (Kupfer, et al., 2021) and from literature such as peer-reviewed articles, reports, and patents. Regarding geography, we utilized site-specific data for assembly at Volvo Cars' engine factory in

Skövde, Sweden, while data on material extraction and manufacturing processes were selected to represent regional averages. Transportation from suppliers to the assembly site was not included. However, in instances where the origin of materials could be identified, we used country-specific or market data representing broader regions. A comprehensive list of the background datasets used in the assessment can be found in the Supporting Information of Paper I.

A life-cycle impact assessment (LCIA) was utilized to explore how the modelling options identify and quantify potential contributions to various environmental impacts. The LCIA allowed us to calculate impact scores for sixteen different impact categories using midpoint characterization methods, as recommended in the European framework of the Environmental Footprint (EF 3.0) (Biganzioli, et al., 2018). More information on the impact categories assessed can be found in Paper I.

The employment of IMDS material data in the calculation of the life cycle inventory (LCI) necessitates a series of steps before the data can be evaluated in the LCIA phase (Figure 3). The generation of comprehensive LCI models for our technical example – the engine – began with the creation of the component material data list as outlined in Section 3.1. Subsequently, materials present in this list and their associated manufacturing and assembly processes were matched to suitable background system datasets. These datasets, primarily selected from commercial LCA databases, contained information on elementary flows which could be translated into environmental impacts in the LCIA phase.

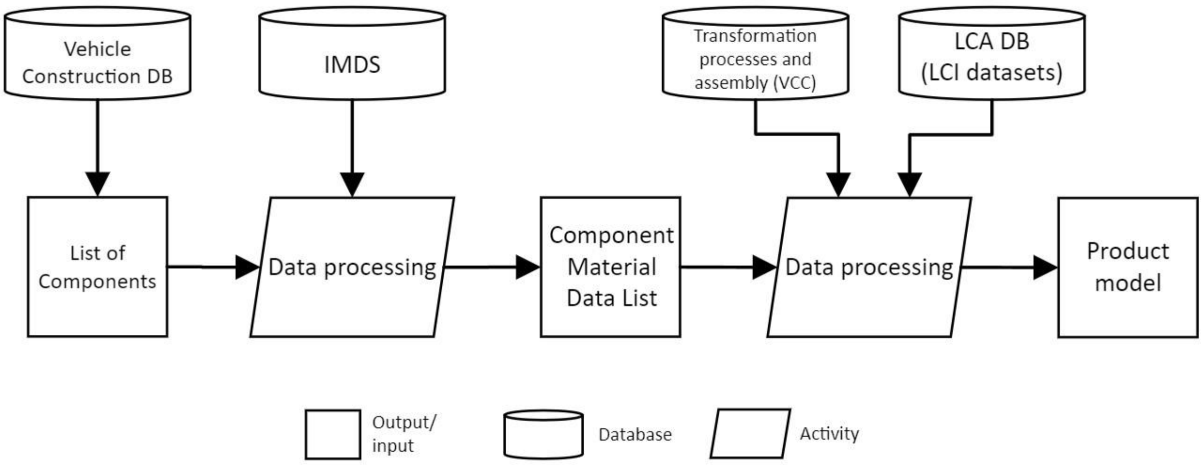

Figure 3. Overview of the steps employed in this study to develop the modelling options for the engine representation.

The component material data list developed for the engine contained 2,156 unique material entries, each composed of one or more basic substances, with a total of 654 unique basic substances identified. In this assessment, these basic substances were matched to background datasets to account for the production of material constituents. Further processing required to achieve finished materials and formed components was accounted for as "manufacturing processes" in the LCI model.

For instance, a material classified as a thermoplastic, composed of polypropylene, glass fibre, and plasticizer, would be matched to background datasets suitable for modelling the production of these three basic substances. This matching process allowed us to account for all the substances that compose every material in the component material data list. Once this matching of the thermoplastic's constituents was done, additional background datasets were incorporated into the models to represent relevant manufacturing processes that combined the basic substances into the more complex material. In the case of thermoplastics, this included compounding, followed by injection moulding.

This two-step matching process allowed us to strive for a higher level of detail in our model by accounting for both the substances that compose materials according to the IMDS data, as well as the manufacturing steps required to transform them into finished materials.

For the final assembly of the engine, we compiled data from Volvo Cars' engine factory in Skövde, Sweden. Most engine parts arrive at this facility in their final form, ready for assembly, except for a few components that undergo specific machining processes on-site, with the engine block being the primary example. The mapping of processes involved and the subsequent linking to background datasets were based on an aggregated data list compiled internally at Volvo Cars. This list contained information on energy consumption (i.e., electricity, heat), auxiliary materials (e.g., cutting fluid), as well as waste and material losses.

It is important to note that, unlike the detailed information on materials and basic substances, data on manufacturing and engine assembly processes, including material losses related to these activities, is not explicitly included in IMDS. In Paper I, we referred to this data as "complementary data", i.e., data which is not directly reported by the component material data list but is essential for the completeness of the LCI model.

A summary of all LCA modelling options assessed in Paper I is presented in Table 2. These options, including the reference option and an additional seven simplified options, differed in their levels of detail. They captured unique combinations of three modelling choices: (i) the function group level employed, which was either "high" or "low" as a means of varying the level of aggregation of IMDS data; (ii) mass cut-off at the material level; and (iii) the number of basic substances representing each material. Both (ii) and (iii) were utilized as a means of varying the level of completeness of the resulting LCI.

Table 2. Summary of the different LCA modelling options assessed in this study.

MODELLING OPTIONS	MODELLING CHOICES			Option name as used in Paper I
	Function group level*	Mass cut-off (of total)	Basic substance per material	
#0 (most detailed)	2 (Sub-parts)	None	many	A100-high
#1	1 (Complete engine)	None	many	A100-low
#2	2 (Sub-parts)	1 %	many	A99-high
#3	1 (Complete engine)	1 %	many	A99-low
#4	2 (Sub-parts)	None	one	B100-high
#5	1 (Complete engine)	None	one	B100-low
#6	2 (Sub-parts)	1 %	one	B99-high
#7 (least detailed)	1 (Complete engine)	1 %	one	B99-low

* Only aggregation levels 1 and 2 are used in this study. See Table 1 for further information on the different function group levels of aggregation.

The modelling options shown in Table 2 were abbreviated in Paper I for conciseness. However, for improved clarity in this thesis, they will be described fully without abbreviations in the following sections. The most detailed modelling option, used as reference, included all engine components, materials, and substances from IMDS, without applying any mass cut-offs (option A100-high in Paper I). This ensured a highly comprehensive representation of the engine's composition. We also assessed simpler models with varying degrees of aggregation and completeness compared to the reference case.

One approach was to model the engine as a single unit (the "low" options in Paper I) rather than separate parts. Other options excluded materials below 1% of the total mass, applied either for the whole engine (A99-low/B99-low options) or for each of the engine's sub-parts (A99-high/B99-high options). Limiting the number of substances representing materials, such as only including the main constituent element, also reduced model complexity (the “B” options). This simplification strategy was applied solely (B100 options) or alongside other strategies. The least detailed option combined all strategies simultaneously (B99-low in Paper I).

Additionally, we explored the influence of complementary data (i.e., data for manufacturing and assembly processes, as well as related material losses) on the results, by running scenarios with and without this information.

In total, we assessed multiple modelling options capturing different combinations of aggregation level, mass cut-offs, substance limitations, and complementary data inclusion. By comparing the results to the detailed reference model, we could assess accuracy losses and workload reductions from the various simplification choices. The findings provided insights into suitable trade-offs based on the specific goals and scope of LCA studies.

3.3 Metal composition and scarcity assessment of vehicle gliders

In Paper II, we identified relevant metals, from a resource availability perspective, for two vehicle gliders and their subsystems. This task was accomplished by employing two indicators of short-term and long-term potential primary metal scarcity. Additionally, we explored the distribution of metals in glider subsystems and components. With this, we aimed to pinpoint substitution options and to evaluate the ease of recycling, thereby facilitating the assessment of the potential availability of secondary metals in the gliders.

The assessed gliders were based on the same car model, a compact sport utility vehicle (SUV). They, however, differed in their equipment levels. One was an extra-equipped glider (EEG), featuring the highest available equipment level, while the other was a standard-equipped glider (SEG) furnished with basic-level equipment.

The first step was to derive material composition data for the assessed vehicle gliders following the procedure described in Section 3.1. The process resulted in two lists, one for each glider. Once the component material data lists were established, we identified the metals present in the gliders by analysing their material constituent entries in the lists, referred to as the basic substances as described in Section 3.2.

Subsequently, we assessed the metals from a supply risk perspective, considering both the short and long-term risks. The short-term supply risk indicator was developed specifically for the study, with the aim of identifying relevant metals in the gliders by assessing their potential scarcity. This indicator is defined as the ratio between the metal demand of a hypothetical glider fleet and the global primary production of the same metal. The hypothetical glider fleet was designed to approximate the annual worldwide production of passenger cars. Hence, this indicator aims to demonstrate how much of the global primary metal would be required if either the extra-equipped glider or the standard-equipped glider options were the sole ones available in the market. We referred to the resulting metric as the “demand fraction of primary production” (DFP) for each metal. A high DFP suggests a potential risk of near-term shortage, with the automotive industry significantly contributing to this shortage.

For assessing long-term metal availability in the gliders, we turned to the literature and utilized the crustal scarcity indicator (CSI) method (Arvidsson, et al., 2020). This mineral resource impact assessment method quantifies the decrease in resource stocks due to extraction, adopting a long-term global perspective on elemental scarcity. The method is premised on the average crustal concentration of elements in the Earth’s crust and, in terms of assessing long-term metal availability, offers several advantages over other resource impact assessment methods (Arvidsson, et al., 2020). The CSI is computed as the product of the crustal scarcity potential (CSP) of a given metal and its mass. In the analysis conducted for Paper II, different metals were grouped according to their overall contribution to the total CSI of the glider; in other words, their share of the glider's total CSI.

To delve deeper into the distribution of metals, we divided the gliders into subsystems using an internal aggregation method adopted by Volvo Cars. This method combines components into larger assemblies performing similar functions, thus creating a hierarchical structure of the vehicle and its constituent parts.[2] This approach aids in identifying subsystems that are more susceptible to supply risks and contribute more significantly to resource demand. In this study, we analysed a total of 21 subsystems, encompassing various areas such as advanced driver assistance, body structures, brake system, and multimedia and communication.

While assessing the distribution of metals in subsystems provides a valuable overview of their presence within the glider, a more detailed examination of the dispersion of metals across individual components can offer further insights. To this end, we investigated the distribution of metals at the component level using the concept of entropy, which serves as both an indicator of the state of disorder in a system and a measure of dispersion (Sethna, 2006). A higher entropy value suggests that a metal is distributed evenly over many components throughout the glider, while a lower value implies a more concentrated presence in specific components.

The entropy information can prove beneficial in determining the effectiveness of various secondary metal recovery strategies. A more uniform distribution of metals may render the extraction of specific metals more challenging. In contrast, a more concentrated distribution is likely to make recycling easier and less costly. Substitution is presumably a more feasible option for scarce metals concentrated in a few components, as opposed to those evenly dispersed across thousands of components.

[2] The internal aggregation method used in this study is an updated variant of the function group classification described in Section 3.2. While similar in its aim to hierarchically combine components performing related functions, the specific aggregation rules differ between the two methods.

4 Results

This section summarizes the results of Papers I and II. Further details are available in the respective papers.

4.1 Extracting material composition data from the IMDS

The extraction of material composition data from the IMDS for use in environmental studies represents a central methodological aspect of this thesis. To facilitate this process, we developed a methodology that has expedited data inventorying for an LCA study by the utilization of IMDS data. This methodology, detailed in Section 3.1, led to the creation of a comprehensive procedure to generate component material data lists, forming the foundation for all subsequent analyses.

The application of this method yielded some key outcomes. Primarily, it established a systematic approach to extract and utilize data from the IMDS. This advancement overcame the limitations traditionally associated with manual data extraction, leading to expedited data inventorying for the assessments conducted in Papers I and II. Additionally, the detailed information contained within the component material data list not only enabled the identification of materials present in vehicles, but also provided insight into the constituent substances of these materials.

Furthermore, the method serves as a foundation for further studies. The generated data lists can be utilized to analyse different aspects of vehicle design, manufacturing, and lifecycle environmental impacts. This broadens the scope of potential research within the industry, allowing for more comprehensive research.

Initially introduced in Paper I, this method proved instrumental in addressing the research questions posed in both papers. This achievement underlines the potential of this methodology to inform future research and environmental strategies in the industry.

4.2 Exploring the use of IMDS data in LCA

4.2.1 Modelling options and workload

In Paper I, we explored the use of IMDS data for life cycle assessment modelling of an automotive engine. The most detailed "reference" model included full component, material, and substance information from IMDS for the engine, and was established as a benchmark for assessing the quality of all other modelling options. This highly detailed model became a starting point for our work, and it was followed by the development of seven less detailed options. As a result, the groundwork done for the reference model, including the matching of basic substances to background datasets and the classification and grouping of material entries, was beneficial for all subsequent options. This led to a significant reduction in workload compared to if they had been developed independently from the reference option.

Table 3 provides an indication of the relative workloads of the different modelling options. The primary factors affecting the workload were the number of materials and basic substances accounted for in the options, and whether complementary data was included. It was clear that a key workload factor for modelling was the careful identification and matching of background datasets to basic substances. This process was pivotal for the study outcome, and in some cases where no suitable background datasets could be found, it became necessary to collect new inventory data, which considerably increased the time required.

Table 3. Modelling options assessed in this study and an estimation of their relative workloads. The names in parentheses refer to the abbreviated options names used in Paper I.

MODELLING OPTIONS	Complementary data	# of unique materials	# of unique basic substances	
#0 (A100-high)	Yes	2,156	654	Workload increases
#1 (A100-low)	Yes	2,156	654	
#0 (A100-high)	No	2,156	654	
#1 (A100-low)	No	2,156	654	
#2 (A99-high)	Yes	671	295	
#3 (A99-low)	Yes	539	243	
#2 (A99-high)	No	671	295	
#3 (A99-low)	No	539	243	
#4 (B100-high)	Yes	2,156	274	
#5 (B100-low)	Yes	2,156	274	
#4 (B100-high)	No	2,156	274	
#5 (B100-low)	No	2,156	274	
#6 (B99-high)	Yes	671	114	
#7 (B99-low)	Yes	539	86	
#6 (B99-high)	No	671	114	Workload decreases
#7 (B99-low)	No	539	86	

It is important to emphasize that the workload necessary to perform the LCI modelling was greatly reduced for all modelling options, once a significant number of materials entries and their inherent basic substances were classified, grouped, and matched to LCI datasets. This information, once compiled, can easily be employed in subsequent LCI modelling but requires continuous updating, as both IMDS data and LCI datasets are frequently updated.

4.2.2 LCIA results

In Paper I we examined different LCIA models with the level of data aggregation and completeness varying across the models. These models were then compared to a reference option, and the results are seen in Table 4.

A key distinction between the models arises from their resolution. Some models assign impacts to specific engine sub-parts, providing a high-resolution view, while others allocate impacts to the engine as a whole, offering a low-resolution perspective. In cases where no material cut-off is applied, high- and low-resolution models produce identical numerical results (options #0 and #1 offer the same LCIA outcomes as do options #4 and #5). Overall, the primary advantage of the high-resolution models lies not in the quantitative outcomes but in the qualitative insights they offer, facilitating a more detailed analysis.

Our findings suggest that when the sole simplification strategy applied is a high-resolution mass cut-off at the material level (#2), there is a smaller deviation in impact scores for most categories than in models where only the number of basic substances representing materials is simplified (#4 and #5). As expected, the most significant differences were observed across most impact categories when both simplifications were used simultaneously (#6 and #7).

The application of the mass cut-off had varying effects based on the resolution level. For low-resolution models, the cut-off was set for the entire engine with a specific mass threshold. Consequently, materials below this threshold were excluded from calculations. In contrast, for high-resolution models, the cut-off was applied to individual engine sub-parts, with varying mass thresholds. This resulted in a higher number of materials being considered in the high-resolution models.

Table 4. Impact scores normalised to the reference option. The colours in the cells vary from "green" (100%) to "yellow" (75%) to "red" (50% and lower). All categories are calculated with midpoint characterisation methods as recommended in the European framework of the Environmental Footprint (Biganzioli, et al., 2018). The names in parentheses refer to the abbreviated options names used in Paper I.

	Modelling options					
Impact categories	**#0 & #1** (A100)	**#2** (A99-high)	**#3** (A99-low)	**#4 & #5** (B100)	**#6** (B99-high)	**#7** (B99-low)
Acidification	100%	89%	87%	88%	77%	75%
Climate change	100%	95%	92%	93%	88%	86%
Ecotoxicity, freshwater	100%	81%	79%	75%	57%	55%
Eutrophication, freshwater	100%	83%	81%	94%	78%	76%
Eutrophication, marine	100%	92%	89%	90%	82%	79%
Eutrophication, terrestrial	100%	91%	89%	84%	75%	73%
Human toxicity, cancer	100%	97%	97%	73%	71%	71%
Human toxicity, non-cancer	100%	91%	90%	82%	74%	72%
Ionising radiation	100%	97%	96%	98%	96%	95%
Land use	100%	94%	93%	73%	68%	66%
Ozone depletion	100%	96%	93%	50%	48%	44%
Particulate matter	100%	96%	95%	79%	75%	74%
Photochemical ozone formation	100%	93%	90%	91%	83%	81%
Resource use, energy carriers	100%	94%	93%	95%	90%	88%
Resource use, mineral and metals	100%	91%	88%	41%	34%	32%
Water scarcity	100%	98%	97%	100%	98%	97%

Table 4 also showcases differences across the various LCIA categories. For four impact categories, including climate change, the calculated impacts decrease by less than 15% between the reference and the most simplified model. However, for the majority of the impact categories, deviations of more than 25% are observed, with the largest discrepancy being 68% for resource use, mineral and metals.

For deeper insights into the impacts of each modelling option, a contribution analysis focusing on two impact categories – climate change and resource use, mineral and metals – is shown in Figure 4. These categories hold strategic importance not only to Volvo Cars but also for the broader automotive sector. Detailed contribution analysis for other impact categories can be found in the Supplementary Information of Paper I.

The analysis indicates that when a mass cut-off is applied at a high resolution as the only simplification strategy, it shows the least deviation in impact scores for climate change and resource use categories compared to our reference model. Predominant contributors to these categories, like steel and aluminium alloys for climate change and steel, aluminium alloys, and copper alloys for resource use, remain largely unaffected by this rule. However, lighter materials such as ceramics, glass, and specific metals like silver, gold, platinum, cobalt, and tungsten are notably impacted by the mass cut-off. This results in a significant reduction in their contributions to the overall impact scores.

In the modelling approach where only the number of substances representing materials is simplified, both the engine's mass and the number of materials included in the model align with the reference model. However, the exclusion of alloying or filler elements in these models introduces notable variations in LCIA outcomes. For instance, in the resource use category, omitting alloying elements from materials such as steel, cast iron, and aluminium, along with the absence of fillers in polymeric materials, results in a marked reduction in relative impact scores compared to our reference model. Conversely, in the climate change category, the lack of these alloying elements leads to a less pronounced, yet still noticeable, deviation, particularly for materials such as steel and cast iron.

The modelling strategy where both simplifications - mass cut-off and substance representation - are applied concurrently deviates considerably from the reference model, not just in the number of materials representing the engine but also in the count of substances representing these materials. This approach results in the most noticeable differences in LCIA outcomes, not just for climate change and resource use, but across various impact categories. Generally, when both simplifications are applied, materials with a lower overall weight in the engine are notably impacted, similar to the strategy where only a mass cut-off is employed. In contrast, heavier materials are typically affected by the reduction in the number of substances representing them, as seen in models where only substance representation is simplified.

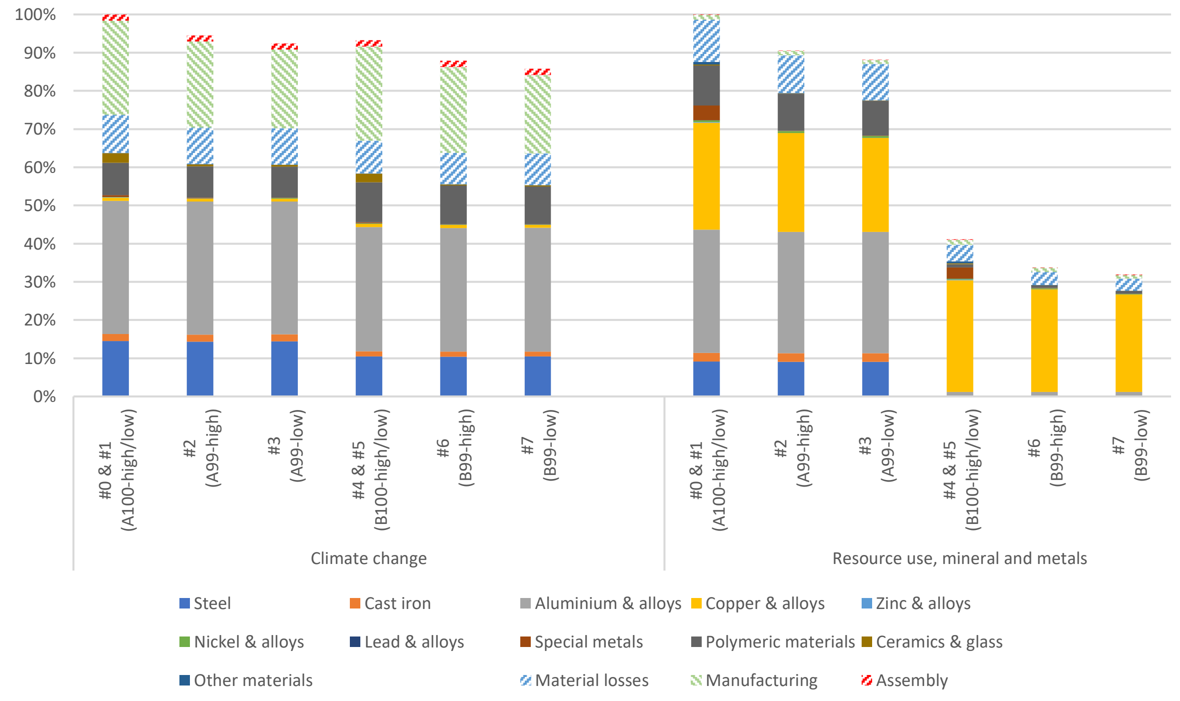

Figure 4. Normalised contribution analysis for two selected impact categories. The material category "special metals" comprises precious and scarce metals. "Other materials" comprises material entries which did not fit into any other material category. "Material losses", "manufacturing" and "assembly" refer to complementary data as described in Section 3.2. All impact categories are calculated with midpoint characterisation methods as recommended in the European framework of the Environmental Footprint (Biganzioli, et al., 2018). The names in parentheses refer to the abbreviated options names used in Paper I.

A key consideration on the influence of data completeness on the precision of LCIA results is the inclusion of complementary data in the LCI models. As stated before, this data, representing information on manufacturing and assembly processes, is absent in IMDS. These processes typically consume substantial amounts of energy, either in the form of electricity for machinery operation or fuel combustion for heat generation. As a result, the integration of this complementary data significantly impacts categories sensitive to electricity production and combustion-related emissions, e.g., climate change.

Delving into the details, the final assembly of the engine makes a minor contribution to most impact categories, with a maximum of 5% across fourteen categories for all modelling options. Conversely, the manufacturing processes of components and sub-parts have a more substantial impact, contributing over 10% across twelve categories for all modelling options. Material losses, which are an intrinsic part of manufacturing and assembly activities, are also factored into the total environmental burden calculation of the engine. The effect of these material losses on impact scores is capped at 11% for the majority of impact categories (13) across all modelling options.

4.3 Assessing metal use and scarcity impacts of vehicle gliders

The analysis carried out in Paper II revealed the presence of a broad range of metals in the assessed vehicle gliders: 55 metals in the extra equipped and 54 in the standard-equipped glider. Notably, gadolinium (Gd) was unique to the extra-equipped glider. While most metals saw increased concentrations in the extra-equipped variant, potassium (K) was an exception. Its reduced concentration in the glider is attributed to decreased mica usage. This extensive diversity of metals highlights the considerable metal requirements of modern vehicles beyond just the powertrain components.

Figure 5 illustrates the mass variations of metals in the extra-equipped glider compared to its standard-equipped counterpart. A detailed observation shows that for nearly half of the metals (27 out of 55), the variation is minimal, remaining below 10%. The vast majority (48 metals) have variations below 100%. However, a specific group of metals, including dysprosium (Dy) and terbium (Tb) gallium (Ga), and germanium (Ge), exhibit much larger variations, with differences reaching up to 25,000%.

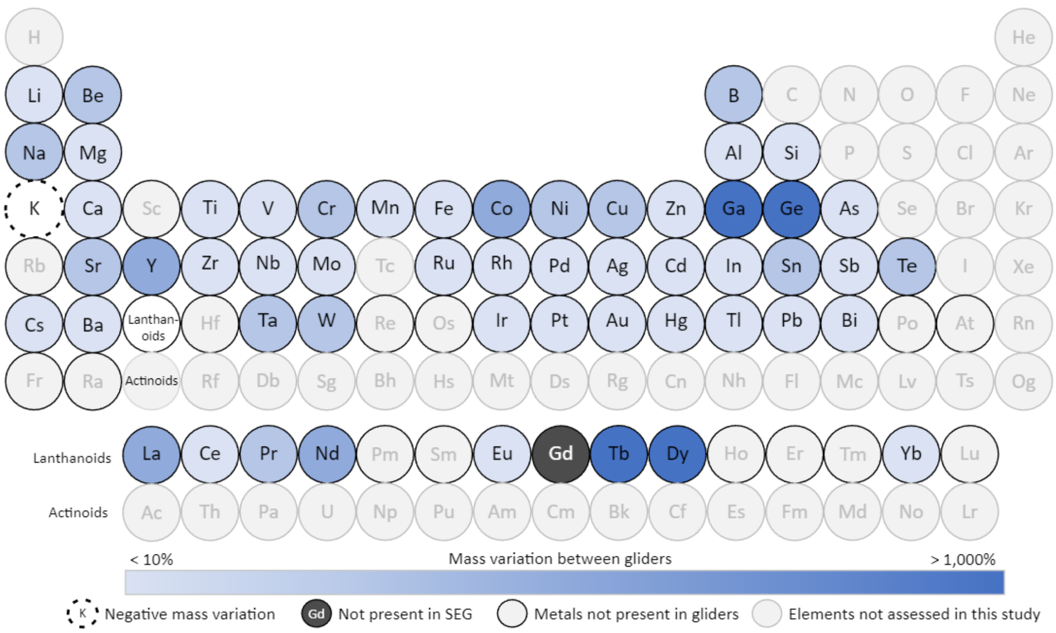

Figure 5. Metals and metalloids in the extra-equipped glider, with mass variation relative to the standard-equipped variant. While potassium (K) appears in reduced quantities in the extra-equipped version, gadolinium (Gd) is absent in the standard-equipped glider.

The results showed that iron and aluminium accounted for around 90% of the total metal mass in the gliders, due to their widespread use in structural and mechanical components. However, the remaining 10% metal mass was distributed among 53 different metals, most of which were present in small quantities. For instance, in the extra-equipped glider, 35 of the 55 metals weighed less than 100 grams each and 19 weighed less than 1 gram.

In Figure 6, we present a dual assessment of metals identified in the extra-equipped glider, with each data point representing a unique metal in this glider. The y-axis plots the short-term scarcity, denoted by its DFP value. This measure captures the portion of global primary metal production a theoretical global glider fleet would demand, reflecting the annual worldwide vehicle production. Conversely, the x-axis depicts the long-term scarcity, indicated by its CSI value, which derives from average crustal concentrations of the respective elements.

Metals identified in the extra-equipped glider are categorized into four distinct groups for ease of visualization: “Red”, “Orange”, “Yellow”, and “Grey”. Metals labelled "Red" face pronounced supply risks in both short and long-term contexts, exemplified by elements such as gold, lead, and copper. The distinction between “Orange” and “Yellow” revolves around their respective CSI shares, though both reflect notable short-term supply concerns. Finally, the “Grey” category denotes metals presenting the least short-term supply risks in this assessment.[3]

Gold, although present in minor quantities (few grams) in the extra-equipped glider, has a substantial impact on the glider’s CSI. In this assessment, gold emerges as the metal with the highest risk of long-term scarcity. As for lead and copper, both are found abundantly in the glider. If such compositions were universal, a fleet of extra-equipped gliders would demand a considerable fraction of global primary production of these metals.

Even with bismuth's low mass content, it plays a notable role in the glider's CSI, displaying elevated potential long-term geological risk. Molybdenum's CSI contribution is similar, even though it has a more abundant presence in the glider – its mass is nearly four times that of bismuth in the extra-equipped glider. When evaluating short-term risks, bismuth has the third largest DFP of all metals assessed, while molybdenum presents a more moderate risk.

A review of rare-earth metals (REMs) in the glider reveals most falling under the “Grey” group, suggesting a reduced supply risk. However, specific metals like terbium (Tb), neodymium (Nd), dysprosium (Dy) and praseodymium (Pr), positioned in the “Yellow” group, indicate potential short-term supply challenges.

[3] For additional details on the colour-coded groups, refer to Paper II.

Figure 6. Assessment of short and long-term potential primary metal scarcity for the metals found in the extra-equipped glider. Short-term potential scarcity is defined by the y-axis, i.e., DFP (demand fraction of primary production) values, while the long-term potential scarcity is defined by the x-axis, i.e., CSI (crustal scarcity indicator) values.

Building upon our earlier discussions on exposure to supply risks, we have undertaken a detailed analysis of the distribution of metals within the extra-equipped glider's various subsystems. Table 5 elucidates this distribution for metals that fall within the “Red”, “Orange”, and “Yellow” categories, with the provided percentages reflecting the relative mass of each metal within the glider.

From the 23 metals under consideration, more than half are predominantly concentrated in the “Multimedia and communication” subsystem, each with proportions surpassing 10%. Remarkably, REMs such as terbium (Tb), dysprosium (Dy), neodymium (Nd), and praseodymium (Pr) showcase significantly elevated mass shares within this subsystem. The principal application of these metals is in the formulation of permanent magnets, predominantly located within the glider's sound system.

“Multimedia and communication” and “Driver controls” exhibit pronounced concentrations of palladium (Pd), tantalum (Ta), and ruthenium (Ru). This can be attributed to the extensive presence of electronic components in these areas. Further, “Electrical infrastructure” subsystem is characterized by the highest mass shares of metals such as copper (Cu) and tin (Sn). Here, copper primarily forms wire harnesses, while tin is a prevalent soldering material.

Silver (Ag), gold (Au), and indium (In) are predominantly housed within the “Exterior visibility” subsystem, utilized for their light-reflecting properties on external mirrors. Pertaining to lightweighting efforts, aluminium (Al) is majorly found in parts such as the wheels, bonnet, bumpers, pillars, and suspension components of the glider. In contrast, most of the glider’s magnesium (Mg) content can be attributed to talc (magnesium silicate) used in plastic components and as magnesium oxide in windscreens.

The dominance of molybdenum (Mo), Niobium (Nb), and Vanadium (V) in the “Body structures” and “Suspension, frames & mountings” subsystems is notable, accounting for nearly 80% of their total mass content in the glider. Their main application is as alloying agents in high-strength steel for structural components. The “Power supply” subsystem houses almost the entirety of the glider’s lead (Pb) content, due to the presence of the lead-acid battery. Meanwhile, bismuth (Bi) is primarily used in paint as a surface treatment for the glider’s exterior, falling under the “Body structures” subsystem.

Table 5. Mass distribution of selected metals present in the different subsystems of the extra-equipped glider. The background colours of each metal – "Red", "Orange" and "Yellow" – represent the groups in which they are classified, as explained earlier in this section.

	Tb	Dy	Ga	Nd	Pr	Sr	Pd	Ta	Ru	Cu	Sn	Ag	Au	In	Mg	Al	Bi	Mo	Nb	V	Pt	Cs	Pb
Multimedia and communication	99%	72%	69%	59%	35%	50%	54%	39%	25%	2%	14%	12%	15%	0%	6%	2%	0%	0%	1%	0%	0%	0%	0%
Doors and boot	0%	27%	30%	14%	15%	9%	0%	1%	0%	2%	3%	1%	0%	0%	3%	1%	0%	4%	11%	5%	0%	0%	0%
Steering	0%	0%	0%	24%	50%	1%	1%	0%	4%	2%	2%	2%	0%	0%	14%	4%	0%	1%	0%	1%	0%	0%	0%
Driver controls	0%	0%	1%	0%	0%	0%	14%	14%	37%	1%	5%	4%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Seating	0%	0%	0%	0%	0%	11%	1%	0%	0%	4%	6%	10%	0%	0%	2%	0%	0%	7%	8%	6%	0%	0%	0%
Electrical infrastructure	0%	0%	0%	0%	0%	0%	4%	11%	6%	71%	21%	16%	2%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%
Exterior visibility	0%	0%	0%	0%	0%	7%	1%	0%	2%	1%	4%	20%	75%	99%	0%	1%	0%	0%	0%	0%	0%	0%	0%
Exterior glass	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	10%	0%	0%	15%	0%	2%	0%	0%	0%	0%	0%	0%
Interior trim and lighting	0%	0%	0%	0%	0%	0%	1%	3%	2%	0%	1%	1%	0%	0%	13%	0%	0%	0%	0%	0%	0%	0%	0%
Exterior trim	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	20%	13%	0%	1%	1%	2%	0%	0%	0%
Wheels, tyres and accessories	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	3%	0%	0%	4%	38%	0%	2%	0%	2%	0%	0%	0%
Body structures	0%	0%	0%	0%	0%	4%	0%	0%	0%	1%	1%	0%	0%	0%	7%	16%	95%	68%	58%	40%	0%	0%	0%
Suspension, frames and mountings	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	1%	0%	0%	0%	1%	13%	1%	11%	18%	38%	0%	0%	0%
Climate	0%	0%	0%	2%	0%	1%	6%	2%	3%	2%	3%	8%	0%	0%	5%	8%	1%	0%	0%	0%	95%	100%	0%
Power supply	0%	0%	0%	0%	0%	6%	0%	0%	0%	6%	17%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	100%
Restraints	1%	0%	0%	0%	0%	4%	5%	6%	4%	1%	2%	1%	1%	0%	0%	1%	0%	1%	2%	2%	5%	0%	0%
Exterior lighting	0%	0%	0%	0%	0%	2%	4%	8%	5%	2%	7%	4%	1%	0%	3%	1%	0%	0%	0%	0%	0%	0%	0%
Brake system	0%	0%	0%	0%	0%	4%	1%	3%	2%	3%	8%	1%	1%	0%	1%	1%	1%	3%	1%	2%	0%	0%	0%
Advanced driver assistance	0%	0%	0%	0%	0%	0%	4%	8%	8%	0%	2%	3%	1%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%
Locking and security electronics	0%	0%	0%	0%	0%	0%	2%	2%	2%	0%	1%	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Instrument panel and console	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	0%	0%	0%	0%	0%

The importance of metal distribution in components plays an important role in influencing the ease of substitution and effectiveness of metal separation in end-of-life vehicles (ELV) prior to implementing recovery approaches like reuse and recycling. In Paper II, the concentration of metals in individual components was analysed using entropy as an indicator, seen in Figure 7.

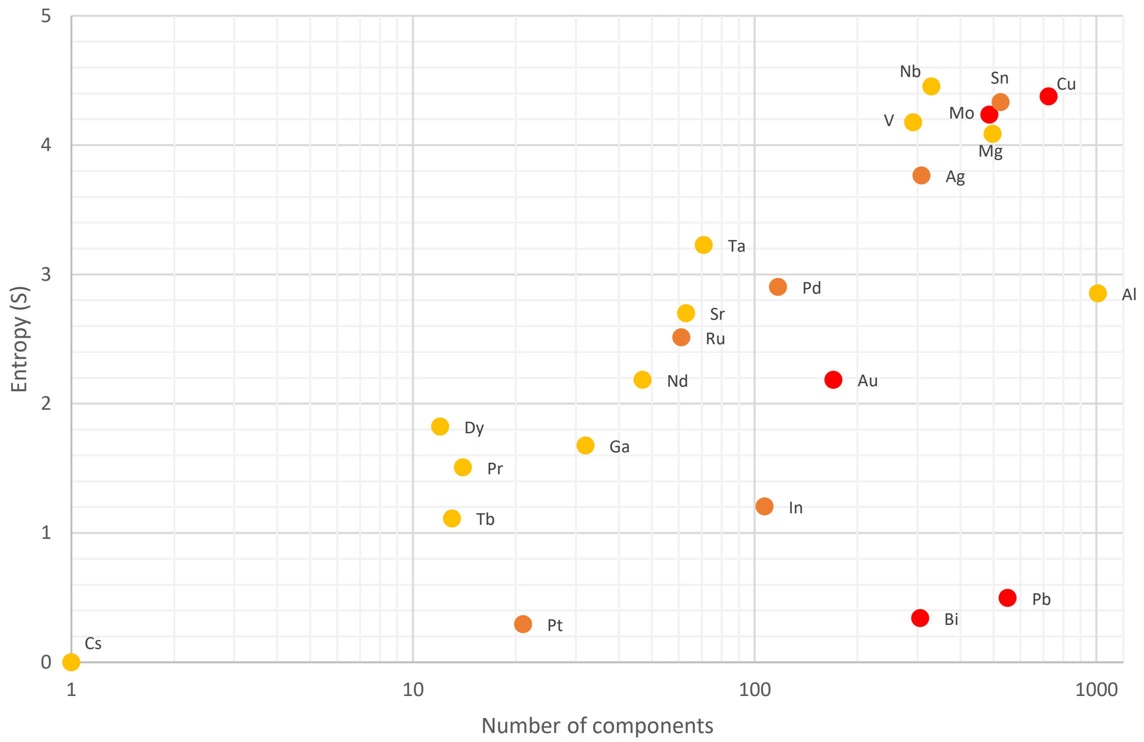

Figure 7. Calculated entropy for selected metals in the extra-equipped glider and the number of components in which these metals are present.

A key observation from Figure 7 is the notably high entropy of copper, found in over 700 components, predominantly as wire harnesses. This implies that its recovery presents significant challenges. Lead offers an interesting contrast. Even though it is part of over 500 components, its entropy is significantly lower than copper, primarily because it is heavily concentrated in the lead-acid battery. Consequently, the separation process for most of the lead becomes more straightforward.

It is worth noting that while some REMs face potential supply disruption risks, their recovery rate from ELVs is currently negligible. Figure 7 hints at the possibility of efficient recovery of certain REMs since they are predominantly found in a limited number of components. For instance, almost all terbium in the extra-equipped glider is confined to merely three components. Hence, focusing on the retrieval from these specific components might enhance the overall recovery rates of such metals.

The metals bismuth (Bi), platinum (Pt), and caesium (Cs) display lower entropy, but their primary uses in applications like paint, conductive paste, and flux pose challenges to their effective recovery. Similarly, gold (Au), silver (Ag), and indium (In) used in mirror coatings present their unique challenges, especially given their widespread distribution and minute overall presence in gliders.

The analysis in Paper II also showed that short-term supply risks varied notably for some metals between the gliders. While the metals in the "Red" and "Orange" groups remained constant despite the gliders' equipment level, the "Yellow" group displayed variance. Notably, metals with reduced quantities in the standard-equipped glider compared to the extra-equipped option display a noticeable decline in their short-term potential scarcity and their global production value contribution, as visualized in Figure 8.

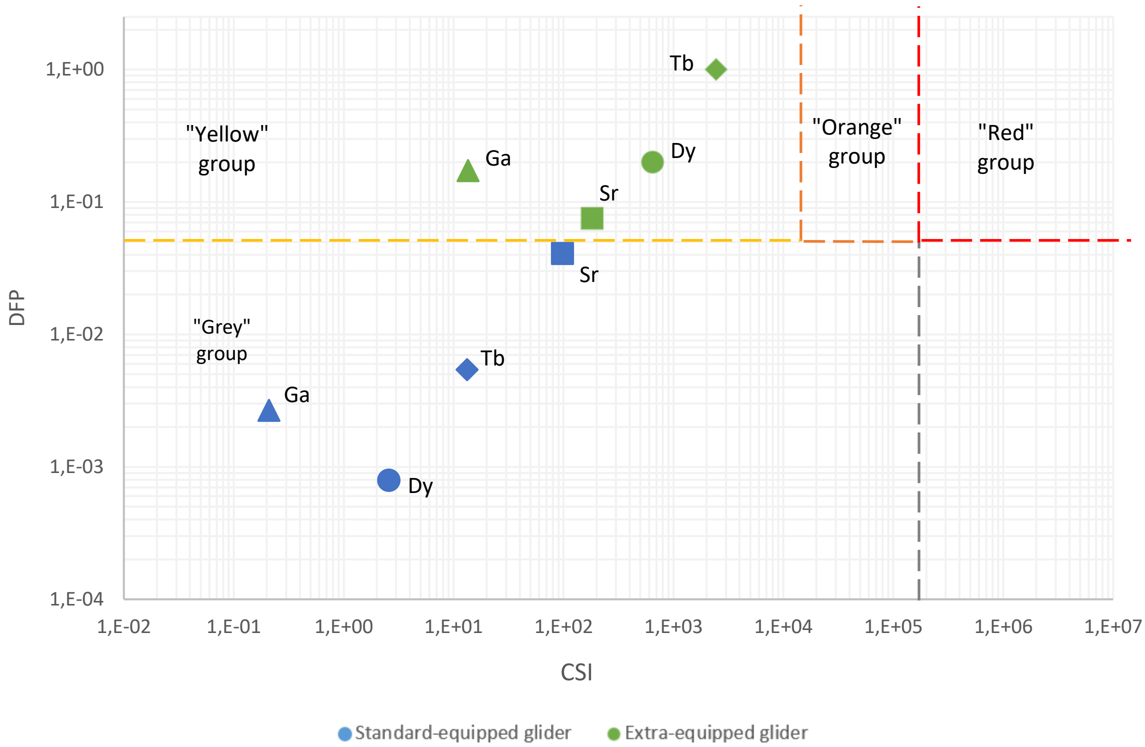

Figure 8. Differences between gliders for selected metals. The metals depicted in the figure are those whose DFP value becomes less than 5% in the standard-equipped glider, i.e., metals which "migrate" from the "Yellow" group in the extra-equipped glider to the "Gray" group in the standard-equipped variant.

As prime examples, dysprosium (Dy), terbium (Tb), and gallium (Ga), saw a significant drop in their short-term primary metal availability indicator when comparing standard-equipped gliders with extra-equipped gliders. For context, a hypothetical global fleet of the latter would necessitate the entirety of the global terbium production, while a fleet of the former would need less than 1% of this global output. These metals, mainly present in permanent magnets in the "Multimedia and communication" subsystem, are substantially more abundant in the extra-equipped glider. Finally, strontium (Sr) transitions from the "Yellow" category in the extra equipped to the "Grey" group in the standard equipped. Unlike dysprosium, terbium and gallium, strontium does not have a significant mass discrepancy between the two glider types, which explains its elevated DFP value in the standard-equipped gliders.

5 Discussion

With the key findings of this thesis presented, this section will synthesize the insights gained and situate the research within the broader context. First, the posed research questions will be revisited to demonstrate how the methods and analyses undertaken have addressed the aims of this thesis. Subsequently, our work will be positioned among other studies and the implications of the findings will be discussed for relevant stakeholders. Finally, potential avenues for future research will be outlined.

5.1 Addressing research questions

RQ1: *How can a method be developed to extract material data from the IMDS that also facilitates expedited data inventorying in environmental studies within the automotive industry?*

To address RQ1, we demonstrated a systematic methodology to extract material composition data from the IMDS database for use in environmental studies. The key steps included extracting a list of all components for the vehicle from Volvo Cars' vehicle construction database, adding material composition data by linking to the IMDS database via an automated algorithm, generating a component material data list with materials and their constituent substances, and finally classifying materials and substances and matching them to appropriate LCI datasets (in the case of LCA studies). This streamlined approach overcomes limitations of manual data extraction, allowing expedited creation of detailed LCI models. The material data lists also support additional analyses beyond LCA. Overall, the method enables leveraging IMDS for accelerated environmental assessments within the automotive industry.

However, it is important to acknowledge certain challenges and limitations associated with this methodology. In Paper I, one primary concern arose during the modelling work, where matching basic substances to background datasets became intricate. The IMDS typically reports substances in their refined form as present in finished vehicle components (e.g., chromium, nickel). However, in real-world production processes, many substances, especially those used as alloying elements in steels, are introduced in their unrefined forms, such as ferrochromium (for chromium) or ferronickel (for nickel). When these unrefined forms are not accurately represented, it can result in overestimations of environmental impacts due to the additional processing steps involved in refining them. Moreover, the IMDS does not provide details about material production routes or the recycled content share. This omission can lead to potential misestimations in environmental impacts, as different materials undergo diverse processing steps with varied recycled content ratios. Gathering precise data on recycled content is further complicated by the myriad of suppliers involved, often resulting in estimates that might not reflect the real situation.

While this method excels in detailed resource use assessment, it may introduce uncertainties in other impact categories. These uncertainties may arise due to the large impact that specific material production routes have on the amounts of emissions (e.g., electric-arc furnace vs blast-oxygen furnace in steel production). The extent of this uncertainty is tied to the (limited) availability of datasets when matching IMDS data to background data.

In Paper II we faced another challenge. In the assessment, we examined the metal content in gliders down to the elemental level. Metals that were identified as part of compounds had their quantities estimated using molecular formulas from their respective CAS (Chemical Abstracts Services) registries in the IMDS. When a registry was missing, experts had to make judgments, which could introduce uncertainties into the findings. Despite of the method's strengths in accelerating environmental assessments, it is crucial to remain aware of its limitations.

RQ2: *How do the level of data aggregation and degree of completeness of an LCI model employing IMDS data affect the precision of environmental impact assessment results and the effort necessary to develop such models?*

For RQ2, we performed LCA modelling of an engine using IMDS data with different levels of aggregation and completeness to assess precision and workload trade-offs. A 1% mass cut-off at the material level maintained reasonable precision for most impact categories while greatly reducing modelling workload. Limiting the number of substances representing materials caused larger deviations across many impact categories but also substantially reduced workload. Unsurprisingly, the simultaneous application of both simplification strategies saved further workload but culminated in the most substantial variances in LCIA outcomes for most of the impact categories examined. Mineral and metal resource utilization emerged as one of the most compromised categories with this method, showing nearly a 70% discrepancy. In contrast, the climate impact exhibited less variation, with deviations under 15%. This combined approach could be reasonable in e.g., a "screening" study looking only at potential contribution to global warming. However, for assessments focused on metal resource use, a higher level of detail is required.

Incorporating manufacturing and assembly data importantly influenced climate change and other energy-related impacts. Modelling with high resolution data offers enhanced comprehension of LCIA results but in most cases did not considerably improved results quantitatively. Moreover, it is crucial to align choices regarding IMDS data aggregation and completeness with the specific LCA goal and scope, as higher detail improves precision but increases workload.

Another important point to highlight is how we measured the modelling workload. Our work started with the modelling of the most detailed modelling option, used as reference. Because of this, models with less detail took advantage of the work already done for the detailed model, making them easier and quicker to develop. Consequently, we were not able to quantitatively assess the time spent on each modelling option and had to base our assessments on reasoning. If exact time measurements were to be done, it would be necessary to use another approach. So, it is worth noting that our estimates on workload are only qualitative estimates.

RQ3: *What is the metal composition of vehicle gliders and how does it differ between different equipment levels?*

The metal composition of vehicle gliders is complex. The analysis of two distinct glider options, with different equipment levels, reveals the presence of around 80% of all naturally occurring metals, which is comparable to complete vehicles when the powertrain is included (Iglesias-Émbil, et al., 2020). This highlights that systems beyond the powertrain contribute significantly to the broad metal demands of the automotive industry.

Iron and aluminium constitute approximately 90% of the total metal mass of the gliders. Interestingly, the remaining 10% is distributed over many different metals (>50 metals), mostly in very small quantities (<100 grams). For half of the metals present in the gliders, the mass variation is under 10% between the standard equipped and the extra-equipped glider. However, four elements – dysprosium, terbium, gallium, and germanium – are found in significantly larger quantities in the extra-equipped option, with variations exceeding 1,000%. Of these, dysprosium and terbium exhibit the most pronounced mass variations: over 25,000% and 18,000%, respectively.

Gadolinium is exclusively present in the extra-equipped glider and potassium is the only metal with a lower concentration in this glider. Overall, while most metals do not vary significantly, some specific metals tied to additional features do show large differences based on equipment levels. This indicates that higher equipment levels may exacerbate supply risks for those metals.

It is important to provide context to these findings based on our study's observations. The gliders we examined might be considered “over-equipped” when compared to other vehicles in the same segment. Yet, prevailing trends in the automotive industry are showing a rise in equipment levels across vehicles (Restrepo, et al., 2017; European Commission, 2022; Trovão, 2022). This trend is driven by factors such as advancements in safety, growing preferences for comfort, the demand for digital connectivity, and the push for automation. As a result, the difference in metal use between standard and more equipped cars may become smaller. Furthermore, this increased equipment demand could lead to the automotive industry relying more on potentially scarce metals.

RQ4: *How do vehicle gliders contribute to the short and long-term potential primary metal scarcity?*

Vehicle gliders, with their diverse metal composition, have a significant impact on the short and long-term scarcity risks of many metals. As cars continue to evolve with features like automation, connectivity, and electrification, the demand for these metals is expected to grow, increasing their scarcity risks (European Commission, 2020a; European Commission, 2022; Trovão, 2022). Therefore, it is also important to consider the usage trends of such metals in the automotive industry and other sectors, to further understand the potential impact of these risks.

Gold, copper, lead, molybdenum, and bismuth face high risks of becoming scarce in both the short- and long-term perspective. Although only a small amount of gold is present in the gliders, it accounts for around 45% of their long-term scarcity risk. And with more cars using gold in electronic components, this could accentuate long-term supply risks.

Copper and lead demand from a theoretical extra-equipped glider fleet would constitute around 10% and 28% of global production, respectively. The surge in the automotive application of copper, especially for electrification components, could further strain its supply chain. While lead shows high recycling rates, still about 40% of the world's lead comes from primary sources (ILZSG, 2022). The sustained reliance on lead-acid batteries in the foreseeable future could potentially exacerbate both its short and long-term scarcity concerns (ITRI, 2017).

For most REMs, the study does not reveal significant long-term supply risks. However, short-term risks are high for some like terbium where an extra-equipped glider fleet would demand its entire global production. Contrarily, standard-equipped gliders show lower scarcity risks for metals like dysprosium, terbium, and gallium. This is because they have fewer permanent magnets than their extra-equipped counterparts.

RQ5: *How does the distribution of metals across subsystems and components in gliders influence the relative complexity of substitution and secondary metal recovery?*

The distribution of metals in gliders strongly influences the complexity of metal substitution and secondary metal recovery strategies, as delineated by the entropy assessment presented in this thesis. Entropy serves as an indicator of the spread or "randomness" of metals across the components of a glider.

Copper exhibits one of the highest entropies. It is found in over 700 components in the gliders, mainly wire harnesses, which poses significant recovery challenges. In fact, a substantial portion of copper in ELVs is not functionally recycled and ends up lost or as contaminants in other recycled metal streams (Center for Automotive Research, 2006; Simic & Dimitrijevic, 2012; Fonseca, et al., 2013; Tasala Gradin, et al., 2013). Our analysis indicates the difficulties in copper separation from diverse material streams, particularly given its extensive distribution in wire harnesses. New techniques for recycling of copper from wire harnesses are being explored to enhance yields (Lu, et al., 2019; Xu, et al., 2019).

Contrasting copper, lead showcases a much lower entropy. Its primary concentration in the lead-acid battery simplifies its separation from the glider. With a well-established recycling process for lead-acid batteries, lead emerges as one of the most recycled metals globally (Ballantyne, et al., 2018).

Although bismuth, platinum and caesium are mostly concentrated in few components, their primary utilization in dissipative applications, including paint and conductive paste, complicates their recovery. Our assessment emphasizes the challenges in segregating these metals from larger concentrations and their recovery inefficiencies due to dissipative uses.

Our assessment also indicates challenges in recovering specific metals such as precious metals and REMs from ELVs. Precious metals, although economically valuable, face recovery challenges primarily due to their low overall masses and their high dispersion across various components. In contrast, REMs not only have low masses but also exhibit relatively low market prices. This does not technically hinder the recycling process, but it does challenge the economic rationale behind recycling especially when considering the costs versus the potential benefits. In fact, REMs recovery from ELVs remains minimal (Andersson, et al., 2017; Restrepo, et al., 2017). In such scenarios, targeted recovery strategies, such as focusing on printed circuit boards (PCBs) for precious metals and on permanent magnets for specific REMs, could potentially enhance their retrieval.

5.2 The results in a wider research context

5.2.1 Using IMDS data in LCA

While our work represents a novel quantitative assessment of the implications of using IMDS data in LCA, prior studies have recognized the potential of IMDS as an efficient data source and developed systematic approaches for data extraction and processing. Koffler, et al. (2008) and Yu & Kim (2013) put forth methodologies to extract material composition information from IMDS and match it with LCI datasets, with the goal of streamlining and expediting LCA modelling compared to manual approaches. There are clear similarities in the overarching aim to leverage IMDS to reduce LCA workload. Additionally, both studies utilize IMDS to compile detailed component and material information as the foundation for LCA inventory data, through automated processes.

However, a key distinction to our work is the attempt to quantitatively evaluate the impacts of using IMDS data on LCA results, by assessing different levels of data aggregation and completeness. These studies have not examined this aspect in such detail. While they present efficient methods for IMDS data extraction, we take an additional step to provide clearer guidance for practitioners on suitable data usage strategies based on study goals. This was achieved through the engine case study, where we analysed the trade-offs between modelling effort and result accuracy under different IMDS data usage scenarios. Therefore, our work builds upon and extends prior research on IMDS in LCA by providing a quantitative perspective on the implications of data quality, completeness and aggregation on LCA outcomes.

More recently, Accardo, et al. (2023) performed a similar investigation on simplification strategies for LCA modelling using IMDS data, but with a driver's seat as their case study. This provides a useful complementary automotive component to analyse compared to our engine study. The authors developed a reference LCA model using the full detailed list of materials and substances from IMDS, mirroring our approach. However, they employed a different set of midpoint characterization methods (CML baseline), analysing 11 impact categories as opposed to our 16. They then assessed the impacts of five cut-off scenarios, a VDA classification scenario, and a one-substance-per-material scenario. The cut-off and one-substance strategies aligned directly with the simplifications we studied. The VDA scenario specifically utilized the material classifications from IMDS to categorize substances, which we did not examine.

Interestingly, their findings on the impacts of mass cut-offs reinforce our conclusions. They found that cut-offs introduced significant deviations in certain impact categories, e.g., abiotic depletion, even at 1%. However, for climate change impacts, mass cut-offs up to 5% did not affect results substantially. This aligns with our finding that small cut-offs maintain reasonable accuracy for carbon footprint assessments. The one-substance approach in their study showed the most pronounced variation in the ozone depletion category. Conversely, other impact categories remained largely unaffected. This contrasts with our results, where the approach corresponding to their one-substance strategy led to significantly larger variations in multiple impact categories, notably in metal resource use.

As for their VDA strategy, it led to a neglection of around 20% of the environmental impacts in the abiotic depletion category, with negligible variation in the other impact categories. Regarding manufacturing data, their results show that material processing stage contributes significantly, over 20%, to climate change impacts. This aligns with our finding that incorporating manufacturing and assembly data importantly influenced climate change and other energy-related impacts. Their overall conclusions complement our findings in demonstrating the clear trade-offs involved in using simplified IMDS data for LCA modelling.

5.2.2 Scarcity assessments in the automotive sector

Several studies have explored the material and metal composition of passenger vehicles. While many of these studies share the objective of identifying and assessing different aspects of metal scarcity, their approaches and data sources differ. Like Iglesias-Émbil, et al. (2020) and Bhuwalka, et al. (2021), we also base our assessment on detailed primary data from automotive manufacturers. However, whereas their focus was on complete vehicles – encompassing both ICE and electrified models – our attention is specifically on gliders, excluding the powertrain.

Iglesias-Émbil, et al. (2020) conducted an in-depth analysis of 60 metals across a conventional ICE vehicle and a battery electric vehicle. The scope of their study aligns closely with ours, both in the number of metals assessed and the detailed examination of metal distribution within vehicle subsystems. Their adoption of an exergy indicator offers a contrasting perspective to our emphasis on short and long-term scarcity metrics. Their findings underscored that the most exergy-intensive metals, including cobalt, nickel, lithium, copper, and aluminium, are predominantly found in the high-voltage battery, electric motor, charger, and power module. This highlights the dominance of powertrain-related components in the metal scarcity assessment of complete vehicles.

Other authors applied a vulnerability assessment to metals present in conventional and electrified vehicles. Knobloch, et al. (2018) assessed 27 metals, and their findings identified, among others, dysprosium, neodymium, terbium, and praseodymium as vulnerable metals, which resonates with our results. Bhuwalka, et al. (2021), on the other hand, took a more expansive approach by examining 76 elements, encompassing most metals. Their study highlighted the changing material demands due to vehicle electrification, emphasizing metals such as cobalt, copper, nickel, aluminium, and neodymium.

As mentioned before, one distinct difference between our study and others is our particular emphasis on gliders versus complete vehicles. This unique perspective offers an alternative approach into the significance of metals across different components and systems beyond the often-discussed powertrain. In fact, this difference in scope might be a significant factor causing variances in the identified critical metals between our findings and those of other studies. Notably, our findings reveal the importance of various metals in subsystems like safety, entertainment, communication equipment and structural components, which often go underrepresented in broader studies. Additionally, our utilization of an entropy indicator aids in gauging the feasibility of metal recovery and substitution.

5.3 Implications for stakeholders

Based on the assessments in Paper I and II, several implications for the automotive sector and other stakeholders emerge.

Use of IMDS data and LCA integration: Building on our discussion from the previous section, the methodology for extracting material composition data from IMDS holds significant value for Volvo Cars. Its broader applications are not limited to streamlining data for LCA studies, as evidenced by the metal scarcity study. While IMDS is invaluable for easing LCA inventory tasks, aligning data extraction and modelling to individual study objectives remains crucial.

Minor materials and result accuracy: While the strategic approach to data simplification can ease modelling, omitting minor materials can jeopardize result accuracy in many impact categories. This especially applies when omitting specific alloying elements.

The value of complementary data: Building on our earlier discussion, extending data sources beyond IMDS is essential. This could include manufacturing data, material loss information, production routes, and recycling content. For a more extensive approach, the automotive sector might consider developing comprehensive internal material databases. Instituting standards on minimum recycled content could enhance data quality.

Increasing dependency and challenges in recovery: As vehicles increasingly integrate advanced technology, reliance on metals like gold, silver, palladium and REMs grows. This transition indicates a potential volatile supply chain, emphasizing the need for sustainable sourcing. Concurrently, the complexity of efficiently recovering these metals, thinly dispersed across multiple components, present noticeable challenges. The low economic value of certain metals adds another layer to the challenges associated to their recycling.

Alternative material sourcing and substitution: The potential scarcity of precious metals, especially gold with its significant long-term scarcity risks, calls for a proactive search for alternatives. Substitution strategies like cladding base metals with gold alloys have been employed successfully to reduce gold usage in electronics (European Commission, 2020b). Beyond gold, the potential scarcity of metals like dysprosium, terbium, and gallium also demands attention. Strategies like the adoption of iron-based permanent magnets could mitigate supply risks. Manufacturers are advised to engage with material scientists and industry experts to scout for potential substitutes that can be seamlessly integrated into production processes without causing disruptions while delivering equivalent or superior functionality compared to the metals they replace.

Evolving vehicle equipment levels: Differences in equipment levels present significant variations in the short-term potential scarcity of several metals. This could have immediate implications for automotive manufacturers who might need to adjust their manufacturing strategies (high vs low equipment levels) based on the availability and predicted scarcities of metals. However, in the long term, the trend of vehicles getting equipped with more advanced features combined with increasing electrification, implies that future vehicles might have a similar metal composition, irrespective of their segment or level of equipment. This could have large impacts on supply chains, urging automakers to re-evaluate their sourcing strategies and establish partnerships to ensure a steady supply.

Geopolitical considerations: Indicated short term supply risks calls attention to a range of factors that might interrupt supply chains. Geopolitical factors, for example, adds additional risk beyond limited global supply that relate to the geographical and political distance between supply and demand. Hence, diversifying sourcing regions, establishing stronger trade relationships, and considering domestic metal reserves can serve as potential strategies to mitigate these risks.

5.4 Future research

In our journey through this thesis, we have explored the potential of IMDS data for environmental assessments in the automotive industry. We tackle not only the complexities of LCA modelling but also delve deep into the metal compositions of vehicle gliders, focusing particularly on metal scarcity. Despite our broad approach there remain areas unexplored, suggesting interesting avenues for future research.

In Paper I, we found that certain simplification strategies might work well when modelling vehicle parts made up of bulk materials, especially for carbon footprint assessments. These strategies seem to retain the accuracy of LCIA results for such assessments. However, the situation becomes more challenging when considering more complex components like power electronics and traction batteries. Our research did not provide detailed guidance for such parts. Accardo, et al. (2023) suggests that the simplification strategies they employed for a vehicle seat could potentially be extended to other components or even the entire vehicle. Yet, they do not offer conclusive evidence for their efficacy. There is a chance that the simplification strategies we used might have different effects on such complex components. This is a clear area for future research. Additionally, the potential of setting up detailed databases for automotive materials is a promising avenue. Such resources could fill in the gaps in material knowledge and make environmental assessments more comprehensive.

In Paper II, we addressed the topic of metal scarcity by focusing on a specific aspect of supply risk. However, to achieve a more comprehensive understanding of the challenges associated with metal availability and use, one must delve deeper into both supply risk and the economic vulnerability of stakeholders. Discussing supply risks involves considering different variables, such as country concentration of production, political stability of producing nations, trade barriers, and recycling rates. Vulnerability, on the other hand, encompasses factors like material substitutability, recyclability, price volatility, and demand growth potential. Exploring these nuances in future research can offer a more comprehensive view of critical metals in the automotive sector.

Throughout our research, various knowledge gaps have emerged, pointing to opportunities for further investigation. A key area focuses on LCA studies of vehicle gliders. Despite the detailed analysis presented in Paper II, there remains a need for more exhaustive evaluations of the environmental impacts of vehicle systems excluding the powertrain. In this regard, contrasting current impacts with historical data might provide insights into the environmental evolution of various vehicle parts, such as specific electronics or sensors. Furthermore, as advancements such as hydrogen-reduced steel become more prominent, it is crucial to consider potential changes in environmental footprints of future vehicles. Similarly, when assessing vehicles with all-electric propulsion systems, it is vital to comprehensively compare the environmental impacts of powertrains to the rest of the vehicle components. For instance, exploring the integration of innovative vehicle designs with emerging propulsion technologies, such as sodium-ion batteries or ferrite-based electric motors, could offer deeper insights into addressing sustainability challenges in the automotive industry.

Finally, while this research has provided valuable insights on key aspects of environmental assessments in the automotive sector, it also sets the ground for broader, as well as more nuanced investigations in the future, taking inspiration from both our missed opportunities and planned projects.

6 Conclusions

This thesis has underlined the potential of IMDS data in aiding environmental assessments within the automotive sector. The approach to extract material composition data from IMDS described in this thesis, enables highly detailed modelling in LCA studies. Yet, certain challenges in the data, such as a lack of information on material production routes and recycling content, may affect the accuracy of environmental impact estimations.

While IMDS proves valuable for LCA, the balance between precision and modelling effort is evident when adopting different modelling simplification strategies. For instance, utilizing a mass cut-off or representing materials by a single basic substance can lead to significant workload reductions. However, there is a trade-off in precision, which becomes especially pertinent when examining impacts related to e.g., mineral and metals resource use.

The in-depth exploration of vehicle gliders' metal compositions underscores the significant influence of their vast metal requirements on the automotive manufacturing supply risks. The interdependencies between the automotive sector and other industries become more evident, as the risk in one can have cascading effects on the other. In our assessment, gold, copper, and certain REMs have emerged as particularly vulnerable to scarcity risks, especially with the growing trends of electronics integration.

The challenges in metal recovery from ELVs, especially for precious metals, copper, and REMs, remain challenging. Factors such as distribution throughout the vehicle, low overall mass of some metals and low economic value make recovery complex. Novel techniques for recycling of wire harnesses can potentially improve copper recovery. Moreover, a better understanding of where specific metals are primarily used, like REMs in multimedia equipment and gold in electronic setups, allows for more focused recovery strategies.

Our assessment notes that differences in equipment configurations lead to significant disparities in the short-term scarcity for some metals. Therefore, developing mitigation strategies like material substitution and efficient ELV recovery will prove critical for the automotive industry's long-term metal sustainability.

Finally, the lessons derived from this research underscore the intricate relationship between data-driven decision-making, like using IMDS, and real-world challenges in the automotive sector. Metal scarcity and recovery issues are intertwined with larger industrial trends, and it is imperative for automotive stakeholders to effectively synthesize this knowledge. Hopefully, the insights gained from this thesis can guide the industry toward a more sustainable use of resources, better equipping it for a more resilient future.

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