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AutoPCM – An automated LLM-based approach to identify potentials for circular design in automotive electronics

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ABSTRACT

The growth of electrical/electronic (E/E) systems in vehicles intensifies the need to address their environmental impacts in the automotive industry. Existing tools for E/E architecture (EEA) development focus mainly on technical implementation, while corresponding environmental frameworks remain insufficiently integrated at the product design level. This paper introduces AutoPCM, an automated Large Language Model-based approach that augments human expertise by transforming manufacturing documents into product architecture decompositions. AutoPCM generates the Physical Component Mapping, a visualisation method for representing automotive electronic product architectures, and evaluates applicable circular strategies following the Eco-Sensitivity Framework, a product-centered view of possible circular strategies for distributed and centralised EEAs. Large Language Models interpret manufacturing documents to extract component relationships and joining technologies, generate clear matrix-based representations of product structures, and convert them into JSON Linked Data (JSON-LD) for circularity assessment. AutoPCM, implemented in Palantir Foundry, is validated on two automotive case studies, a headlight electronic control unit and a camera sensor, achieving high performance with F1 scores of 0.93–1.0 for matrix heading and 0.82–0.95 for joint coding. The approach enables real-time sustainability feedback, supporting designers and decision-makers in optimising EEAs for the circular economy.

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1. Introduction

With continuously increasing demands for electrical/electronic (E/E) systems implemented into vehicles, the automotive industry must address the electronic-specific resource depletion, navigate supply chain uncertainties, and manage raw material price volatility (Fotouhi et al. 2016). In addition, manufacturers are subject to market and governmental pressure to reduce their environmental impacts, making circular principles a key strategy. Regulatory frameworks such as the European Green Deal (European Commission and Directorate 2021) and the End-of-Life Vehicle Directive (European Commission and Directorate – General for Environment 2023a) are pushing manufacturers and suppliers to integrate circular

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economy principles throughout the vehicle lifecycle to reduce environmental impacts and exploit ecological potential.

Even with the growing importance of circularity for automotive electronics, current tools for the development of vehicle electronics forming the E/E architecture (EEA) focus mainly on technical implementation. In contrast, the few existing conceptual methods for circularity evaluation lack a connection to the product design level. For this reason, the Physical Component Mapping (PCM) and the Eco-Sensitivity Framework (ESF) were introduced (Peitzmeier et al. 2025) to provide a structured means of analysing product architectures and deriving design-dependent circular strategies for distributed and centralised EEAs. However, both require expert knowledge and significant manual effort in their application. This reliance on manual execution is especially restrictive in the context of the ongoing transition toward centralised EEAs, where functional and economic value is consolidated in fewer hardware units and early design decisions strongly determine circularity potential.

With recent advancements in artificial intelligence, particularly Large Language Models (LLMs), promising capabilities for automating complex product analysis tasks from product documentation exist (Koh 2024). Following this development, this work addresses the expert-intensive and manual use of PCM and ESF by introducing AutoPCM, an automated LLM-based workflow that transforms text-based manufacturing documents into actionable design insights. AutoPCM generates matrix representations of product structures, evaluates joining technologies regarding the efforts for disassembly and reassembly, and assesses circular strategies for E/E products and components following the ESF. The approach bridges the gap between circular economy principles and practical design implementation, providing designers and decision-makers with automated insights into applicable circular strategies from reuse to recycle at various levels such as vehicle, product, and component. The use of LLMs for the processing of diverse, heterogeneous data to represent the product structure, including joint evaluation and the subsequent rule-based evaluation of applicable circular economy strategies, makes this approach flexible in its fields of application while remaining comprehensible. The methodology is validated through two industry case studies, demonstrating its applicability in real-world scenarios. The key contributions of this work are:

- **Automated generation of the Physical Component Mapping**: A novel LLM-powered pipeline that extracts component relationships and joining mechanisms by processing structured and unstructured text data, such as bills of materials and assembly instructions of automotive EEAs.
- **Circularity assessment integration:** Embedding of the Eco-Sensitivity Framework as a rule-based decision tree for applicable design-dependent circularity strategies on the product, circuit, and component levels.
- **Semantic interoperability:** Representation of the product structure in JSON-LD format to enable automated reasoning and knowledge graph integration.
- **Validation through automotive case studies:** Application of the approach to an automotive headlight control unit and a camera sensor, showing high accuracy and significant time savings.

Figure 1 provides an overview of AutoPCM, illustrating its role in circularity assessment and design optimisation of automotive E/E products.

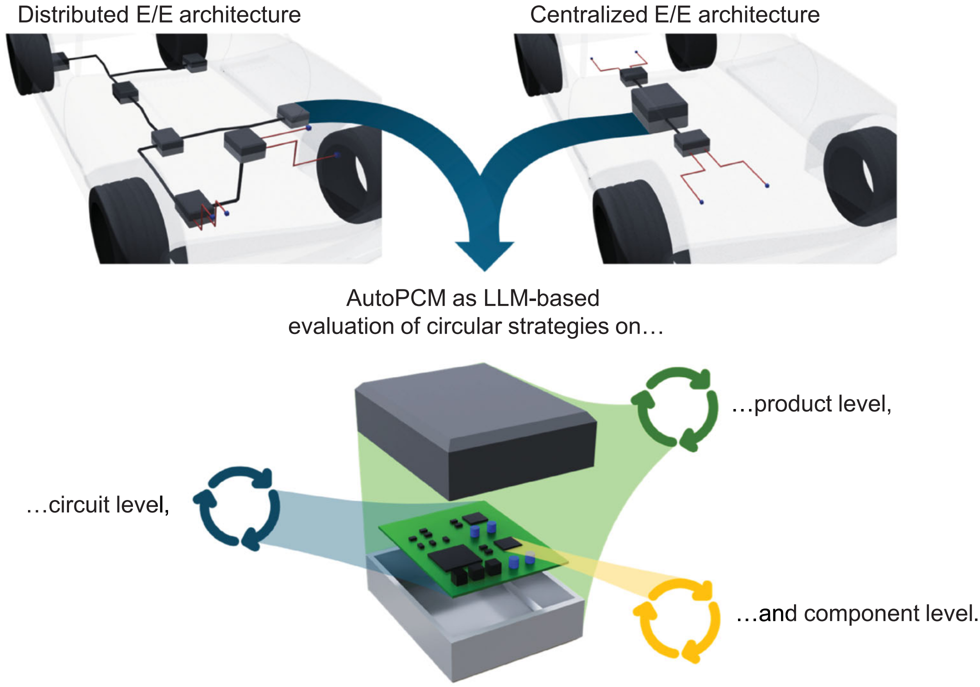

Figure 1. AutoPCM as a method for circularity assessment and design optimisation of automotive E/E products.

2. Related work

The following section reviews the state of the art and introduces the conceptual baseline that informs the proposed automated approach.

2.1. State of the art

The state of the art is grouped into three parts relevant to this study: (1) circular design frameworks in automotive and electronics, (2) the architectural evolution of automotive E/E systems, and (3) the automation of product structure representations.

Even though the regulatory pressure to be environmentally sound is increasing (European Commission and Directorate 2021; European Commission and Directorate – General for Environment 2023a; European Commission and Directorate – General for Environment 2023b), the automotive industry struggles with the implementation of circular approaches (Schöggl et al. 2024). In this context, the comprehensive circular framework introduced by Aguilar Esteva et al. (2021) addresses the material, manufacturing, usage, and end-of-life phases of automobiles. However, it provides guidance primarily at an industry-wide level rather than at the product design level. The DigiPrime KPI framework, proposed by Kanellou et al. (2021), gathers all relevant KPIs that need to be monitored on a macro-level along a supply chain when closed loop strategies are implemented in the automotive industry. Schleusener et al. (2025) propose a framework for multi-criteria evaluation of possible circular economy paths for automotive components. A digital hub was developed to support circular collaboration inside the automotive industry (Remke et al. 2025). Further circularity principles and frameworks applied in the automotive context focus on specific components of the automobile, such as electric motors (Di Gerlando et al. 2024), power electronics (Alatise et al. 2025; Rebenklau 2025), batteries (Cruz Ugalde and Talens Peiró 2024; Dunn et al. 2021; Picatoste, Justel, and Mendoza 2022), body parts (Prochatzki et al. 2023), and materials in general (Luo, Apelian, and Taub 2025), as well as metals (Alcoceba-Pascual et al. 2025) and plastics (Baldassarre et al. 2025; Matos et al. 2023). Fontana et al. (2024) present a manual decision-making framework for circular strategies for vehicle electronics, which can be used by stakeholders along the value chain. In addition, they present a framework for life cycle sustainability and circularity assessment (Fontana et al. 2025). Cozza, D'Adamo, and Rosa (2023) examine the recycling of printed circuit boards from vehicles as a single circular economy strategy factor for economic development. In summary, there are several circular frameworks and studies for various vehicle products. This applies to a limited extent to electronics, but no explicit focus is placed on the automotive EEA evolution and its hierarchical application from the product to the component level.

The integration of software and electronics into vehicles is getting increasingly important, as vehicles are evolving from unique technical features towards functionalities such as comfort, connectivity, safety, and automated driving (Kuhnert, Stuermer, and Koster 2025). This challenges the currently prevalent distributed EEA design with electronic control units (ECUs) being responsible for individual functions in terms of data load, functional safety, computing power, feature dependencies, development and maintenance costs, error rate, as well as modularity and flexibility (Mauser and Wagner 2024). Distributed EEAs overload modern vehicles with more than 100 ECUs, resulting in complex wiring harnesses and systems that are rigid and difficult to update. Therefore, integrating multiple vehicle functions into a single ECU is the primary method for reducing the overall number of separate units (Bello et al. 2019). The consolidation creates vehicle domains that are controlled by a single dedicated control unit (Wang et al. 2022). A parallel development is the implementation of zonal ECUs, where the controlled functions are divided not by domain but by physical location in the vehicle. Both aim for centralisation with a High-Performance Computing Unit (HPCU) as the main computing unit within the vehicle controlling all functions. This also requires the decoupling of software and hardware, which are still very closely intertwined in distributed systems. Given the continued growth of the automotive electronics market (Burkacky, Deichmann, and Stein 2019), the monetary value embedded within vehicles will increasingly be concentrated in HPCUs and the associated sensors/actuators. In combination with decoupled hardware and software solutions, HPCUs are becoming promising candidates for more sophisticated circular strategies than recycling or thermal recovery, including potentials for design changes and adaptations. Evaluation and design methodologies specifically for the properties of EEAs exist in the fields of embedded software modelling (Askaripoor, Mueller, and Knoll 2024), software reuse (Phadnis, Feyerabend, and Axmann 2024), update capabilities (Zhai et al. 2024), energy demands (Chretien et al. 2013), and further economic and technical metrics (Kanajan et al. 2006; Popp et al. 2007), but do not address the physical component properties and dependencies or their environmental impacts and circular economy potentials.

To keep an EEA as well as its subassemblies and components within the value creation of the circular economy, adapted design choices are required. Design strategies such as

'Design for X' (X = disassembly, recycling, reuse, remanufacturing, etc.) provide recommendations to optimise a product according to the desired strategy (Kuo, Huang, and Zhang 2001). Modularisation and easy disassembly are key properties for bringing a product or its components back into a cycle (Breimann et al. 2023; Flipsen, Bakker, and de Pauw 2020). Depending on the targeted circular strategy, a non-damaging procedure can be relevant for disassembly and reassembly if the product or component is intended to retain its functionality. Since this is mainly determined by the joining processes defined in product development, the selection of joining technologies must be aligned accordingly. For recycling, studies in (De Fazio et al. 2021; Ishii and Lee 1996; Kroll and Hanft 1998) focus on the evaluation of disassembly time, types of tools, and types of fasteners. Favi et al. (2017) propose four quantified circularity metrics for the evaluation of component reuse, remanufacturing, recycling, and incineration. Based on the scoring, designers can improve the product structure or joint selection. However, the level of granularity is missing, as it only suggests changes to fasteners or product structure, without providing precise guidance.

The above works emphasise why architectural decisions matter for circularity, but they implicitly assume the availability of detailed product structure representations. This shifts the focus toward methods capable of generating such representations efficiently.

2.2. Conceptual baseline for automation

As a baseline for automated design analysis, a machine-readable representation of product structures is needed. The Design Structure Matrix (DSM) is a well-established method that can be used for the visualisation and analysis of complex systems (Browning 2016). Therefore, it serves as the baseline for PCM-based analysis. A DSM represents interdependencies between a product's components by marking the relevant cells in an N^2-matrix. Creating a DSM is highly time-consuming for complex products. Manually building the matrix for an 84-component digital printing unit alone took approximately 140 person-hours (Koh 2024). Therefore, automated approaches are needed and are already partly available. Gopsill et al. (2016) generate DSMs based on product evolution. Approaches for automated DSM creation are proposed based on a model-based systems engineering approach (Pons, Cordero, and Vingerhoeds 2021), the utilisation of LLMs (Koh 2024), and the processing of CAD-Data (Wang et al. 2022). However, none of the approaches fully automate the creation of the DSM from product-attached documents such as the bills of materials or assembly instructions. To date, no work has leveraged LLMs' contextual knowledge to enrich the DSM with circularity information extracted from documents, such as component types and joint properties.

3. AutoPCM workflow

3.1. Overview of PCM and ESF

Since a single DSM for a complex product or even an entire system, such as the EEA, can quickly become very confusing and potentially overwhelming for the user, Peitzmeier et al. (2025) introduced a system model called 'Physical Component Mapping' (PCM) for describing and visualising the physical product structure of vehicle EEAs including its ECUs/HPCUs, sensors, and actuators (see Figure 2). With a defined layer structure and multiple matrices,

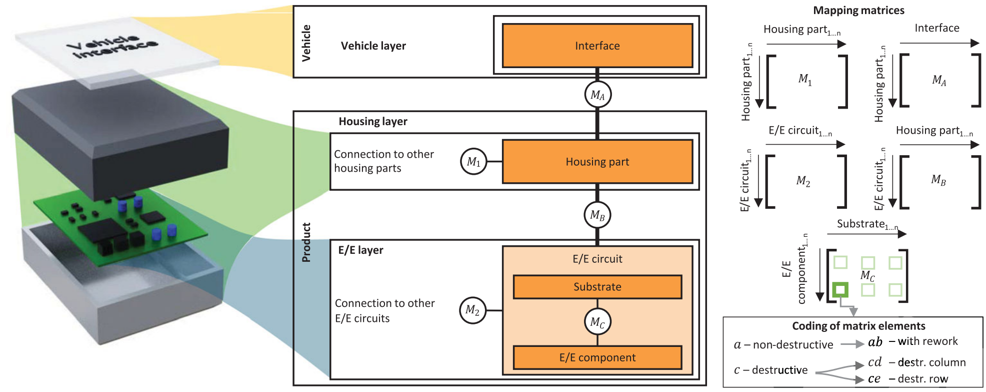

Figure 2. Physical Component Mapping for visualisation of the component dependencies within an EEA (adapted from (Peitzmeier et al. 2025)).

the interdependencies between EEA products and their internal structure, from mechanical to E/E level, can be represented. In addition, it is possible to record which joints damage the parts and which joints limit access to underlying parts.

The system model for the PCM comprises five matrices: M_A describes the connection between the vehicle and E/E products, M_1 includes all mechanical components of the products that are mapped to the housing layer, M_B forms a bridge between housing and E/E layer, while M_2 connects electrical circuits that combine substrates with conductive traces and E/E components (described by M_C) (Peitzmeier et al. 2025).

Compared to a classic DSM, the PCM system model is designed to map distributed and centralised EEA architectures with multiple products simultaneously and to visualise hierarchical dependencies in the physical decomposition. Additionally, it extends the DSM by including disassembly and reassembly information about component connections.

The Eco-Sensitivity Framework (ESF), also proposed in (Peitzmeier et al. 2025), provides guidance on possible circular strategies for both distributed and centralised EEAs on the product and component level (see Figure 3). The ESF shows product and component flows under ideal design assumptions. As the strategies depend on component accessibility as defined by the product design, a design analysis provided by the PCM is needed. Even though these combined methods are considered helpful analytical tools, their manual application is a time-consuming task that requires expert knowledge. Therefore, this work proposes an automated workflow for PCM generation, including the product-level assessment of possible circular paths within the ESF, to guide and accelerate the integration of circular strategies into the development of future vehicle EEAs.

3.2. LLM-assisted workflow

To make the PCM and ESF widely applicable, the approach demands flexible analysis capabilities for documents. As the PCM does not only display the existence of a physical dependency between two components but also provides information about the type of connection, detailed product information is needed. Manufacturing documents such as the bills of materials and assembly instructions can provide this data. Although the information

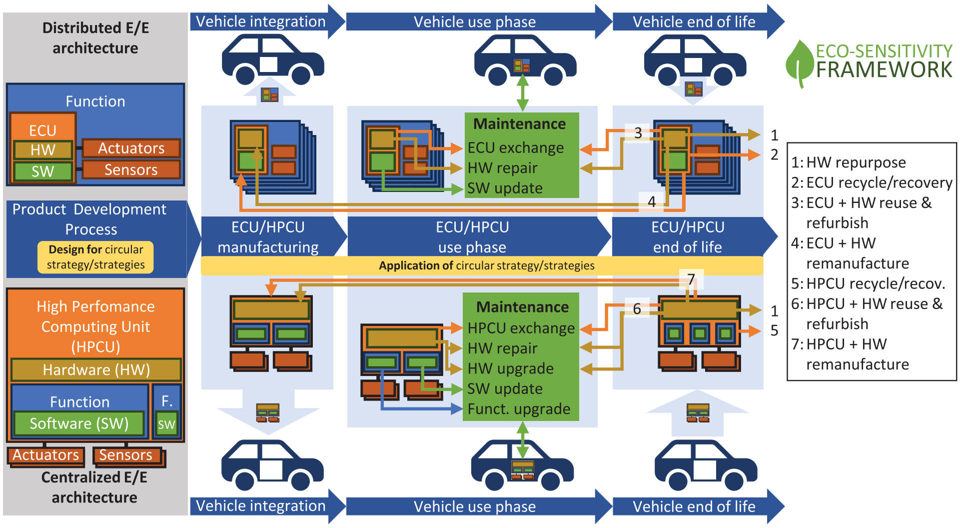

Figure 3. Eco-Sensitivity Framework displaying applicable circular strategies for distributed and centralised EEAs (adapted from (Peitzmeier et al. 2025)).

content in the bills of materials and assembly documents is the same across different companies, each document follows its own layout and standards for description. This makes it difficult to use conventional text extraction methods, such as rule-based regular expressions or template matching. Since Koh (2024) has shown the capabilities of off-the-shelf LLMs to create DSMs from text data, we follow their approach for the PCM automation and extend it to component-type identification and damage assessment. Furthermore, LLMs offer the possibility of incorporating company-specific information regarding joining techniques into prompts without the need for time-consuming programming. Considering sustainability concerns arising from the resource-intensive training and use of LLMs, this work evaluates the application of models of different sizes to minimise the impact as much as possible.

The end-to-end approach for the creation of the PCM and the analysis of possible circular strategies within the ESF contains four main tasks as displayed in Figure 4: Layer assignment, matrix creation, joint evaluation, and the analysis of possible circular strategies. LLMs are used as parsers for the first three phases to translate heterogeneous technical documents into structured, machine-readable representations, while the analysis of applicable circular strategies follows a rule-based decision tree. This produces fully traceable decision paths.

The LLM-based PCM approach is implemented in Palantir Foundry (2025), leveraging its no-code environment and integrated AI capabilities. Foundry's modular workflow builder enables the orchestration of the three pipeline stages – component filtering, matrix creation, and joint coding – without custom code, while its native support for multiple LLM providers (e. g., OpenAI GPT, Anthropic Claude, Google Gemini) allowes flexible model selection per stage.

For the initial creation of the dependency matrices, three LLM blocks are created as displayed in Figure 5. For each block, a defined prompt workflow is proposed (see Appendix I,

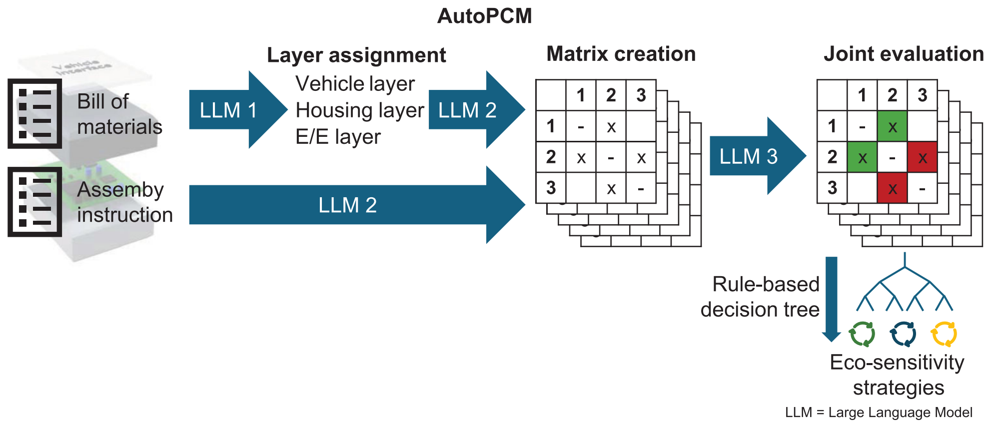

Figure 4. Key stages of AutoPCM to automate the Physical Component Mapping and the Eco-Sensitivity Framework.

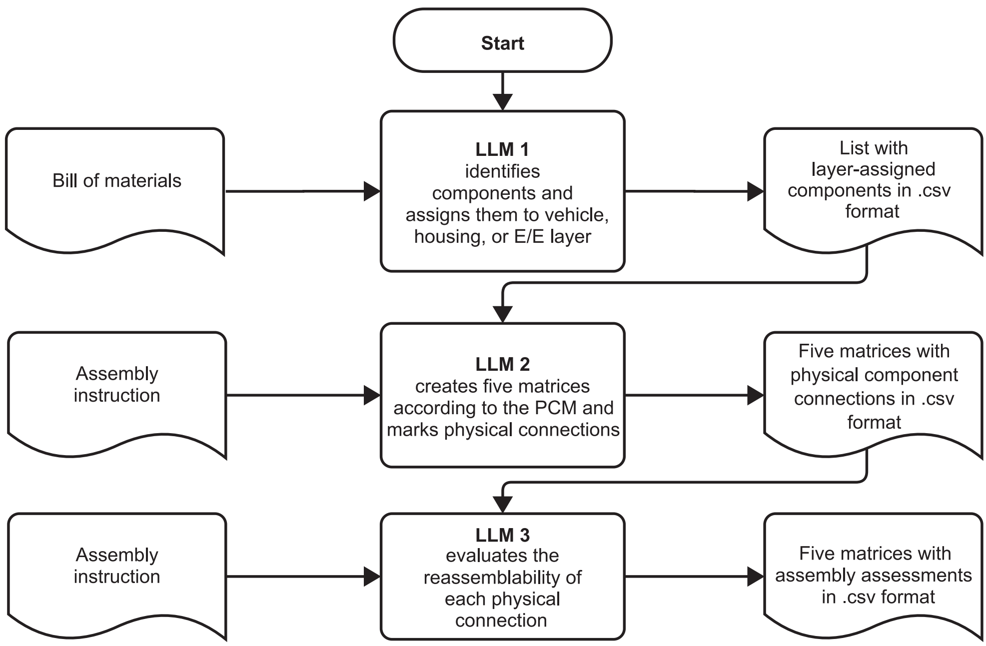

Figure 5. Flowchart of the multi-staged prompting strategy for the creation of the Physical Component Mapping.

II, and III). LLM 1 filters the input bill of materials and excludes all non-product relevant entries such as process information, assemblies, and joining materials, which are not present in the targeted product representation. Additionally, LLM 1 uses its world knowledge to assign the filtered product components either to the housing or the E/E layer within the PCM. The filtered and extended bill of materials is saved in CSV format.

LLM 2 creates the five mapping matrices defined in the PCM by considering the output of LLM 1 and the assembly manual provided as a PDF file. The prompt for LLM 2 defines

Table 1. Knowledge statements about joining mechanisms and their influence on component integrity.

Joining mechanism	Influence on the component integrity
Screws	'Non-destructive' unless otherwise specified, such as tamper-proof or one-time use
Snap fits	'Non-destructive' if designed for repeated assembly/disassembly; 'destructive' if one-time use or prone to breakage, or 'destructive column'/'destructive row' if a specific part is likely to break. This should be inferred from the context if not explicitly stated.
Glue/adhesives	Depends on the adhesion and cohesion properties of the glue as well as the material properties of the joined components. Strong adhesives are more likely to damage components during separation. Softer materials, such as plastics, are damaged more quickly than hard materials, such as metals.
Soldering	Reassembly is possible with 'rework' (desoldering and resoldering).
Welding/permanent bonding	'Destructive'
Push-fit/friction fit	Flexible connections and parts joined without any additional tool or exceptional force are 'non-destructive'. Joints that require significant force to be disassembled are likely 'destructive'.
Gaskets/seals	'Non-destructive with rework' if replacement is required upon disassembly
Connectors (electrical)	'Non-destructive'

the matrix layout of the five PCM matrices, but the columns and rows (hereafter referred to as matrix headings) are filled automatically by the LLM, followed by the annotation of the physical connections with binary (yes/no) coding in the matrix cells (i. e., matrix entries) based on the assembly instructions.

LLM 3 takes the created matrices as input, evaluates the assembly instructions, and annotates the matrix entries identified by LLM 2 regarding the PCM coding (e. g., destructive/non-destructive). Two different settings are implemented. The first setting includes an evaluation based on the world knowledge provided by each of the LLMs. The second setting includes statements in the prompt about the influence of joining processes on the integrity of the components involved (see Table 1). The three-part structure enables a clear division of tasks and the evaluation of the individual steps of part identification, matrix heading assignment, and the correct coding of matrix entries. To verify that the three-step approach is not only advantageous for evaluating the individual steps but also achieves better performance overall, an alternative single-prompt approach is also investigated, in which a single LLM is assigned all three tasks.

Additional validation checks are implemented in each LLM stage to reduce error propagation. For this purpose, rule-based queries are inserted to check the LLMs' outputs before the actual final output (Table 2). For evaluation, the AutoPCM results are validated against expert–derived ground truth obtained from manual disassembly studies and corresponding PCMs. These expert references are used to evaluate the generated matrices, joint codings, and derived circularity strategies using standard performance metrics such as precision, recall, and the F1 score.

Precision measures the proportion of correctly assigned components (TP) among all components predicted ($TP + FP$) to belong to a specific layer:

$$Precision = \frac{TP}{TP + FP}. \tag{1}$$

Recall quantifies the proportion of correctly identified components (TP) out of all actual components belonging to that layer ($TP + FN$), indicating the model's ability to capture

Table 2. Self-correction queries for performance improvement of the LLM pipeline.

LLM stage	Self-correction queries
Component identification and layer assignment	–
Matrix headings and entry creation	1. Have all parts mentioned in the bill of materials been considered and correctly assigned to their respective layers and matrices? 2. Are the connections accurately represented according to the assembly instructions and inference rules? 3. Are the matrices in the correct order ({*M_A*}, {*M_1*}, {*M_B*}, {*M_2*}, {*M_C*})? 4. Are the matrices correctly formatted and aligned (the first cell is always empty)? 5. Is the output strictly in CSV format for all five matrices, with extra text only provided to explain decisions where 'probably' was selected?
Joint assessment	1. Output only the five modified matrices in CSV format. 2. Each matrix should be a separate CSV block.

relevant items:

$$Recall = \frac{TP}{TP + FN}. \tag{2}$$

The F1 score is the harmonic mean of a model's precision and recall, providing a single score that balances these two metrics:

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}. \tag{3}$$

3.3. Model selection strategy in the multi-stage LLM pipeline

AutoPCM decomposes a heterogeneous engineering task into three stages with different uncertainty profiles, reasoning depth requirements, and error sensitivities. Therefore, a single model strategy is disadvantageous. Component filtering and layer assignment (Stage 1) primarily rely on categorical classification and domain nomenclature, whereas matrix creation (Stage 2) requires relational reasoning across documents, and joint coding (Stage 3) demands interpretation of assembly semantics and material behaviour. The selection of a suitable LLM follows a strategy that prioritises accuracy first, followed by cost and latency considerations. For each pipeline stage, we first establish the highest accuracy (F1 score) among all candidate models on the corresponding task. We then select the model with the lowest cost and highest speed.

3.4. JSON-LD representation and ESF automation

While CSV files provided by the LLMs allow adequate manual evaluation of the LLMs' performance due to their simplicity and human readability, the tabular structure is limited for machine-readable representation of nested product structures or joint relationships. This necessitates either multiple files or complex foreign-key relationships to identify possible strategies. To allow lightweight processing of the product structure, the JSON-LD data structure is well suited for representing physical product structures ("JSON-LD – JSON for Linked Data" 2025). JSON-LD's native support for graph structures and bidirectional linkages provides integration with Resource Description Framework (RDF) triple stores and knowledge graph databases, eliminating the need for multiple relational joins and custom logic implementations that would be required with CSV-based approaches. JSON-LD represents a product's components and joints as interconnected nodes. The approach yields a compact JSON-LD representation and stable, resolvable Internationalized Resource Identifiers (IRIs) for all resources.

For the PCM, the JSON-LD @context declares classes (pcf:Entity and pcf:Join), object properties (pcf:hasJoin, pcf:joins, pcf:damages), datatype properties (pcf:matrix and pcf:joinCode), and labels (rdfs:label). The class pcf:Entity represents components appearing as row/column headings in the CSV matrices, which are linked to other components via pcf:hasJoin. The class pcf:Join represents a single CSV matrix cell including its join coding. It involves the following attributes and relations:

- pcf:matrix ∈ {'M_A', 'M_1', 'M_B', 'M_2', 'M_C'};
- pcf:joinCode ∈ {'a', 'ab', 'cd', 'ce', 'c'};
- pcf:joins → the target component ({'@id': ''});
- pcf:damages → zero, one, or two damaged components ({'@id': ''} list).

Conversion of a CSV matrix into a JSON-LD begins with parsing its headings and grid content. The system determines the row and column entities, creating or merging existing pcf:Entity nodes for all headings. For every existing joint in the grid, the script constructs a pcf:Join node, populating it with pcf:matrix and pcf:joinCode. It links this new join to the corresponding column entity via pcf:joins, and if the join code is destructive, it also computes and records pcf:damages. The pcf:Joint is then attached to the row entity using pcf:hasJoint. When processing multiple matrices, the script merges the individual graphs by reusing the initial @context and concatenating the nodes. A simple duplicate-filtering mechanism is implemented to ensure data integrity.

Figure 6 displays the transformation from CSV into JSON-LD with an exemplary 2 × 2 matrix including partly damaging codings 'cd' and 'ce.' Notably, the labels 'cd' and 'ce', which define unilateral damage when the connection is disassembled, restore the symmetry of the matrix, as both joints in Example.jsonld identify Part B as damaged.

3.4.1. Decision logic

Complementary to the PCM, the ESF provides strategic guidance on applicable circular strategies. We present a rule-based decision tree for distributed and centralised architectures based on the design characteristics of the product in Figure 7. A rule-based approach was chosen to guarantee that the identification of applicable circular strategies remains transparent, interpretable, and traceable, as required for engineering and sustainability evaluations. The decision tree distinguishes three structural levels – product, PCB, and E/E component – each with its own access conditions and applicable strategies. Strategy feasibility depends on the non-destructive disassemblability of the products parts, as defined according to the PCM by matrices M_A, M_1, M_B, M_2, and M_C. The evaluation is implemented in a Python programme that processes the JSON-LD knowledge graph by applying direction-aware gates over matrix-specific joins.

If the product cannot be removed from the vehicle interface (M_A), no product-level strategy except low-level material recycling as part of vehicle disposal is possible. If the product can be removed but cannot be opened without damaging itself or its internal components

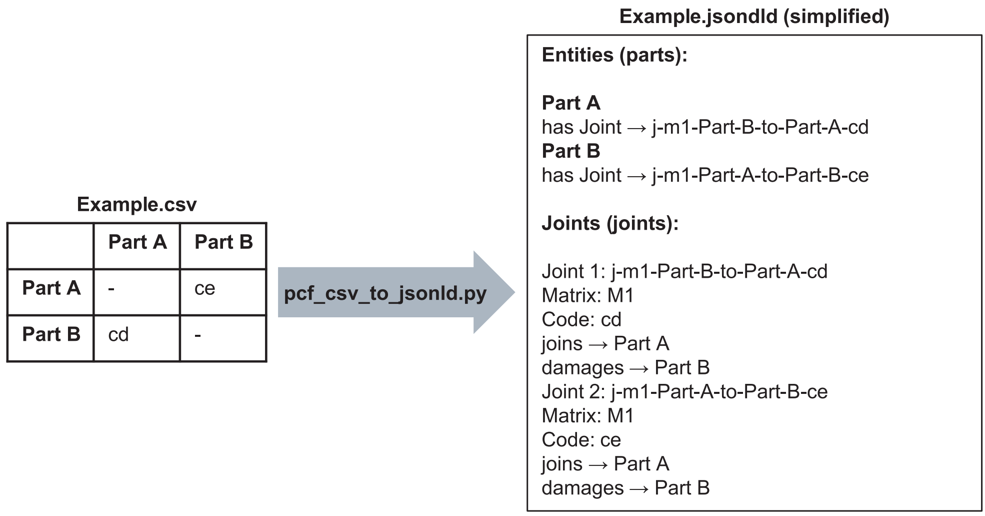

Figure 6. Translation from a CSV matrix to a node representation in simplified JSON-LD.

(M_1), it can be reused as a spare part or repurposed as a complete unit, while material recycling remains a fallback option. If the housing layer allows non-destructive access to its components, reuse, repair, and refurbish are possible. If the design allows damage-free access to underlaying PCBs (M_B), and internal E/E components cannot be detached without damage (M_2, M_C), product-– and PCB-level reuse, refurbishing, or non-invasive repair are possible (e. g., cleaning, resealing, minor fixes). If the internal E/E components are detachable without damage (M_2, M_C), product-, PCB-, and component-level reuse, repurposing, refurbishing, as well as remanufacturing become feasible. Recycling is always a fallback strategy at both the product and component levels when higher-order strategies are not viable. However, the quality of material recycling depends on joint design.

4. Test case 1: electronic control unit for automotive headlights

This section documents a test case that examines the feasibility of using the proposed automated end-to-end approach to generate the PCM and the possible circular strategies derived from the ESF for an automotive headlight ECU. The product's bill of materials is derived from a manual disassembly study and can be found in Table 3. The number and type of electrical components are reduced for the sake of readability. Table 4 presents the assembly steps of the headlight ECU in text form, formulated based on the disassembly study.

The performance of the LLMs' capability to create the PCM is measured against a manually created ground truth displayed in Figure 8. The disassembly study reveals non-destructive disassembly between the vehicle interface and the housing, as well as between the sealing and the housing, in matrix {M_2}. However, the glued connection between the upper and lower housing cannot be opened without damaging the upper housing. In addition, the connection between the housing and the E/E layer, represented by the lower housing and the PCB, is irreversible, which causes damage to the PCB (matrix {M_B}). Within the E/E layer, the E/E components and connectors are soldered to the PCB, which – while

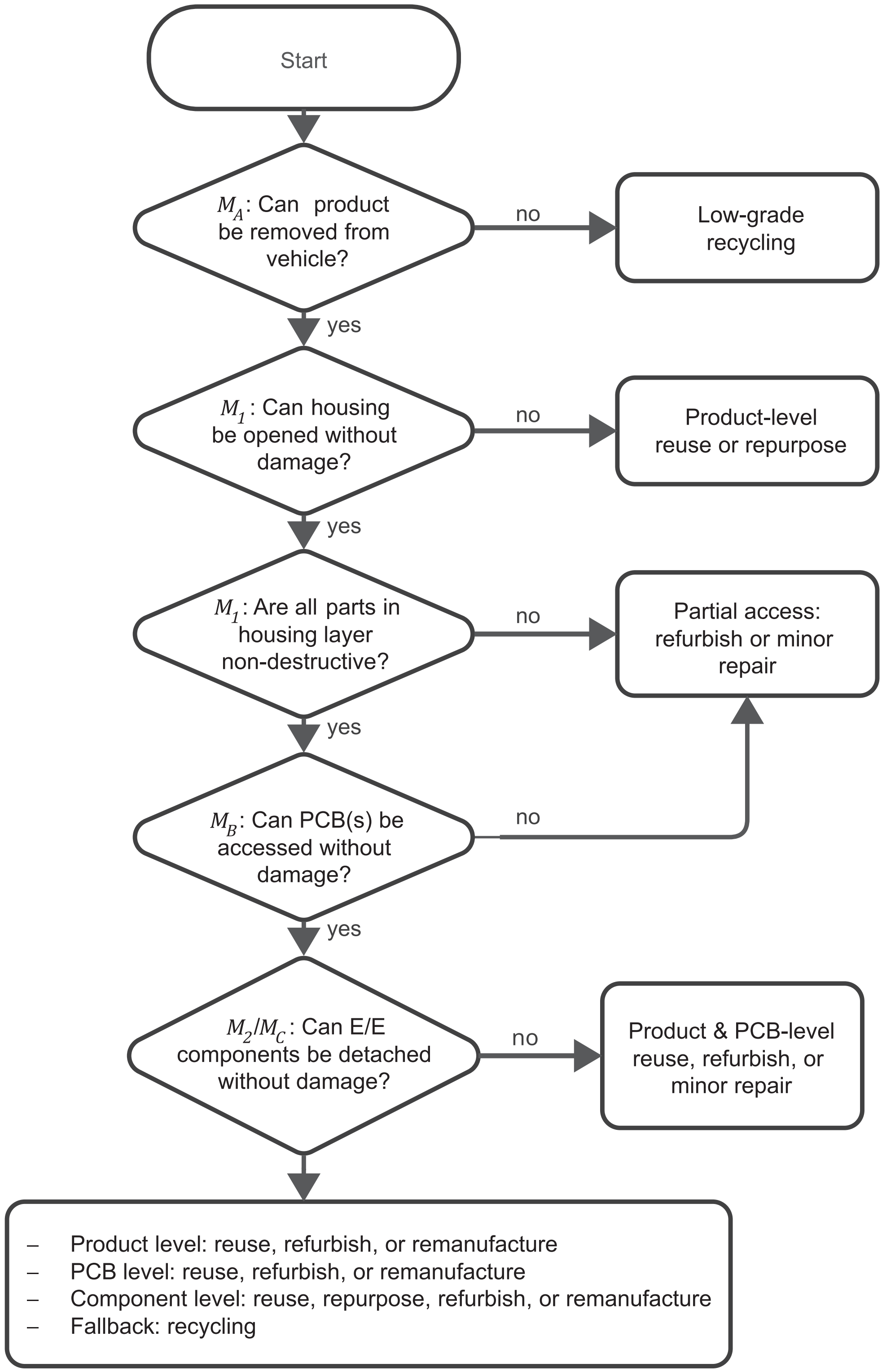

Figure 7. Rule-based decision tree to identify design-dependent circular strategies.

Table 3. Bill of materials for an automotive headlight electronic control unit.

Level	Type	Part number	Amount	Part name	Material
1	Assembly	1	1	E/E architecture ZSB*	–
2	Part	1.1	1	Vehicle interface	–
2	Assembly	1.2	1	Housing ZSB*	–
3	Part	1.2.1	1	Seal	Rubber
3	Assembly	1.2.2	1	Sub-housing ZSB*	–
4	Part	1.2.2.1	1	Upper housing	Plastic (PBA)
4	Assembly	1.2.2.2	1	Lower housing ZSB*	–
5	Part	1.2.2.2.1	1	Lower housing	Aluminium
5	Assembly	1.2.2.2.2	1	PCBA ZSB*	–
6	Part	1.2.2.2.2.1	1	PCB	FR4
6	Part	1.2.2.2.2.2	5	IC logic type	Silicon
6	Part	1.2.2.2.2.3	10	Transistor	Silicon
6	Part	1.2.2.2.2.4	2	Capacitor	Ceramic
6	Part	1.2.2.2.2.5	4	Diode	Silicon
6	**	1.2.2.2.2.*	**	**	**
6	Process	1.2.2.2.2.6	1	Soldering	–
7	Connecting part	1.2.2.2.2.6.1	1	Solder paste	Solder paste
5	Process	1.2.2.2.3	1	Gluing	–
6	Connecting part	1.2.2.2.3.1	1	Silicon-based glue	Silicone-based glue
4	Process	1.2.2.3	1	Gluing	–
5	Connecting part	1.2.2.3.1	1	Silicon-based glue	Silicone-based glue
3	Process	1.2.3	1	Plugged	–
4	Connecting part	1.2.3.1	1	–	–
2	Process	1.3	1	Screwing	–
3	Connecting part	1.3.1	4	M3 × 20 screw	Metal

*ZSB = Assembly **Other soldered components are hidden for readability.

Table 4. Text-based assembly instructions for the headlight electronic control unit.

Step	Description
1	Solder all electrical components onto the PCB.
2	Apply glue to the inside of the lower housing.
3	Position the PCB inside the glue in the lower housing and fix it with two screws.
4	Apply glue to the outer rim of the lower housing and push the upper housing onto it until the snap fits lock in.
5	Pull the rubber seal over the connector part of the upper housing.
6	Plug the connector part of the housing into the vehicle interface and secure it with screws.

disassemblable without damage – require rework. Due to limited accessibility of the electronics inside the ECU, ECU recycling/recovery as well as ECU reuse and refurbishing are identified as applicable strategies within the ESF.

4.1. AutoPCM creation

In the initial step of the analysis, the bill of materials is filtered to isolate all relevant components that define the product structure. Each identified component is then mapped to one of three predefined layers based on its nomenclature and functional context: the vehicle layer, the housing layer, or the E/E layer. This structured classification enables a clear understanding of the product architecture. Table 5 summarises the comparative results of different LLMs applied to the bill of materials from Table 3, highlighting their respective

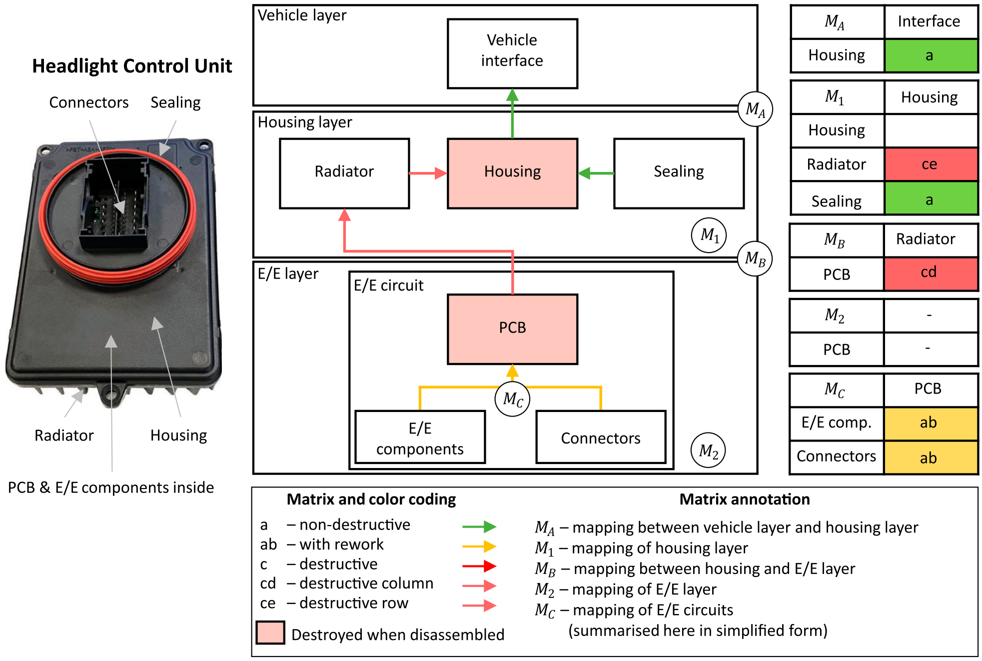

Figure 8. Manual application of the proposed methodology on a headlight control unit (left) as ground truth: Physical Component Mapping showing the product architecture and joint design in graphical (centre) and matrix (right) representations (adapted from (Peitzmeier et al. 2025)).

Table 5. Results of various LLMs on component identification and layer assignment.

Model	GPT-4.1	GPT-4.1 mini	Claude 4 Sonnet	Gemini 2.0 Flash	Gemini 2.5 Flash
Model class	Heavyweight	Lightweight	Heavyweight	Lightweight	Lightweight
Cost	Medium	Low	Medium	Low	Low
Speed	Medium	High	Medium	High	High
Precision	1	1	1	1	1
Recall	1	1	1	1	1
F1 score	1	1	1	1	1

performance in component identification and layer assignment. Except for OpenAI's GPT-4.1 nano, all models were able to identify the relevant entries in the bill of materials and align them to the correct layer. The mentioned cost and speed values are taken from Palantir Foundry. Taking these results into account, GPT-4.1 mini and Gemini 2.5 Flash are the preferred models, as they deliver satisfactory results despite their small size.

The identified and assigned components must now be entered into the five predefined matrices of the PCM. In the prompt, it is precisely specified in which matrix each part of the product/architecture is to be mapped. The assignment of the respective components to the matrix headings and the matrix entries is the task of LLM 2 and is evaluated against the ground truth in Table 6. As GPT-4.1 performs best, its results are forwarded to LLM 3.

Based on the results of the previous LLM blocks, the evaluation of the identified matrix elements according to the PCM coding is conducted by LLM 3. The assessment is carried out in Table 7 once using the plain LLM models and once incorporating the extra knowledge on joining technologies provided in Table 1.

Table 6. Results of various LLMs on matrix creation including headings and entries.

Model	GPT-4.1	GPT-4.1 mini	Claude 4 Sonnet	Gemini 2.0 Flash	Gemini 2.5 Flash
Matrix headings					
Precision	0.93	0.93	0.92	1	1
Recall	1	0.93	0.79	0.93	0.93
F1 score	**0.97**	0.93	0.85	0.96	0.96
Matrix entries					
Precision	0.91	1	0.83	1	1
Recall	1	0.8	0.56	0.8	0.8
F1 score	**0.95**	0.89	0.67	0.89	0.89

Table 7. Results of various LLMs on joint assessment without and with additional information provided in the prompt.

		Model				
Input data		GPT-4.1	GPT-4.1 mini	Claude 4 Sonnet	Gemini 2.0 Flash	Gemini 2.5 Flash
Without Table 1	Precision	0.3	0.35	0.2	0.3	0.2
	Recall	1	1	1	1	1
	F1 score	0.46	**0.52**	0.33	0.46	0.33
With Table 1	Precision	0.75	0.95	0.94	0.65	0.9
	Recall	1	1	1	1	1
	F1 score	0.86	**0.97**	**0.97**	0.79	0.95

Table 8. Cumulative evaluation of the end-to-end workflow.

	Stage	Creation of	Precision	Recall	F1 Score
AutoPCM	1	Layer assignment	1	1	1
	2	Matrix heading	0.87	1	0.93
	2	Matrix entries	1	0.8	0.88
	3	Joint assessment	0.88	0.78	0.82
AutoDSM (Koh 2024) with GPT4.1	2	Matrix entries	0.77	1	0.87
Single prompt with GPT-4.1 mini	1–3	Matrix heading	0.87	0.93	0.9
		Matrix entries & joint assessment	0.81	0.62	0.7
Single prompt with GPT-4.1	1–3	Matrix heading	0.88	1	0.93
		Matrix entries & joint assessment	0.72	0.68	0.7

4.2. End-to-end performance of LLM workflow

In the previous section, the performance of each LLM stage was assessed using ground truth input data. To evaluate the full pipeline, the output from one stage is used as the input for the next. The stages are all handled by the best-performing model: the first stage by Gemini 2.5 Flash, the second by GPT-4.1, and the third by GPT-4.1 mini. The error introduced during the first and second stages is inevitable and propagates directly into the third stage's matrix entry coding, affecting the final output's accuracy. Table 8 shows the stage-wise results of the AutoPCM pipeline and compares the performance with a single-prompt strategy using GPT-4.1 mini and GPT-4.1, as well as with AutoDSM (Koh 2024), an existing approach for automated product matrix creation. The performance comparison with AutoDSM can only be carried out to a limited extent. Whereas the approach focuses on single matrix creation based on data such as handbooks, AutoPCM includes multi-matrix generation and joint assessment based on bills of materials and assembly instructions. Therefore, only the creation of matrix entries (Stage 2) is compared.

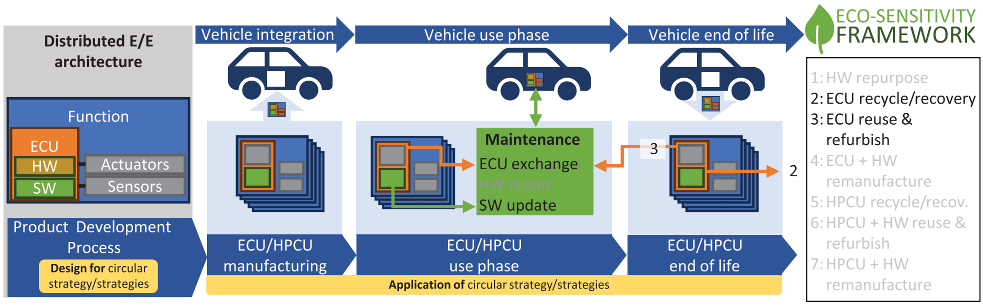

Figure 9. Applicable strategies for the examined headlight electronic control unit (adapted from (Peitzmeier et al. 2025)).

4.3. Automated Eco-Sensitivity Framework analysis

The automated evaluation applies the ESF using a four-gate logic (M_A, M_1, M_B, M_2/M_C) to assess circular strategies for the headlight ECU. The M_A gate (vehicle interface) passed cleanly, indicating non-destructive accessibility at the interface level. However, the {M_1} gate failed due to a destructive joint between the upper and lower housing that damages the former. Similarly, the M_B gate failed because of a destructive joint involving the PCB and the lower housing. The M_2/M_C gate passed, suggesting that downstream detachability is not a limiting factor. Consequently, the feasible strategies are restricted to reuse and repurposing of the full ECU, with recycling as a fallback, while higher-value options such as refurbishing, repair, and remanufacturing are excluded (see Figure Figure 9). This highlights housing and PCB integrity as critical design constraints.

5. Test case 2: camera for automotive safety systems

The second product examined is a camera sensor, which is part of a vehicle's surround view system. It is chosen to evaluate the AutoPCM approach, as it is more complex and provides multiple parts on each PCM layer. Mounted inside the rear-view mirrors, the camera captures the outside of the vehicle. A disassembly study reveals the manually created PCM shown in Figure 10 as ground truth. The bill of materials as well as the assembly instructions are created in a similar way to Test Case 1. The housing layer consists of three housing parts, one of which is non-separably connected to the camera lens. Two seals provide ingress protection. Inside the housing, three PCBs are interconnected and equipped with different E/E components. PCB 1 is fixed with screws, whereas the other two PCBs are glued to the housing. The created bill of materials (Appendix IV) and the assembly instruction (Appendix V) serve the as input for the AutoPCM approach from Section 3.2.

5.1. Automated Physical Component Mapping

Five LLMs with different parameter sizes and computational efforts (cost and speed) are investigated with the AutoPCM workflow. The results for each individual LLM stage fed with ground truth data are shown in Table 9. The results for the AutoPCM pipeline with GPT-4.1 mini for all three stages are compared with an overall single-prompt approach using GPT

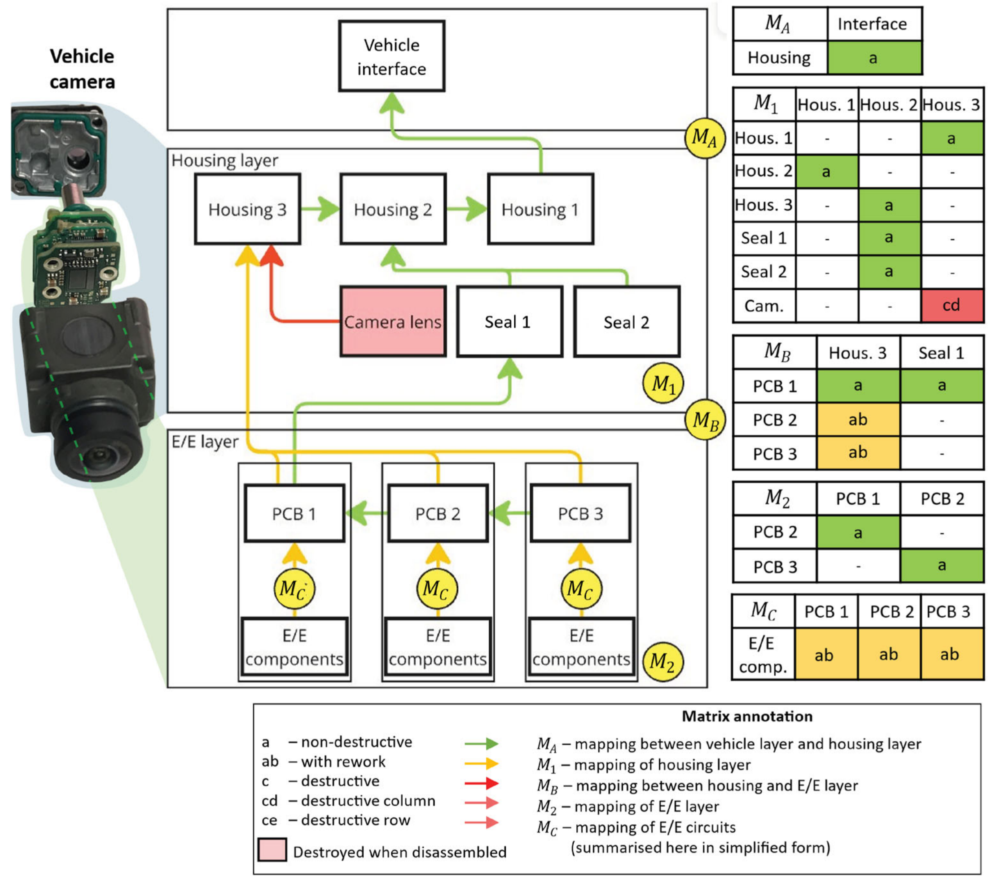

Figure 10. Manually created ground truth Physical Component Mapping of an automotive camera sensor (left) with graphical (centre) and matrix representations (right).

4.1 mini and GPT-4.1 in Table 10. A comparison with the state-of-the-art approach AutoDSM (Koh 2024) is also conducted.

5.2. *Automated Eco-Sensitivity Framework analysis*

The automated evaluation applies the ESF four-gate logic (M_A, M_1, M_B, M_2/M_C) to the vehicle camera sensor assembly. The M_A gate confirmed non-destructive accessibility at the vehicle interface, the $\{M_1\}$ gate indicated that housing components can be detached without damage, the M_B gate showed that PCB integrity is preserved, and the M_2/M_C gate confirmed that downstream components are separable without destructive effects. The only destructive connection identified is between Housing 3 and Camera lens. However, this does not hinder access to the inner components. Consequently, the full spectrum of circular strategies – reuse, repurpose, refurbish, repair, and remanufacture – remain feasible at the product, PCB, and component levels, with recycling as a fallback.

Table 9. Results of the LLM workflow for the automated creation of the Physical Component Mapping for an automotive camera sensor. Each LLM stage is fed with ground truth data.

LLM stage	Model	GPT-4.1	GPT-4.1 mini	Claude 4 Sonnet	Gemini 2.0 Flash	Gemini 2.5 Flash
1	Model class	Heavyweight	Lightweight	Heavyweight	Lightweight	Lightweight
Component	Cost	Medium	Low	Medium	Low	Low
identification and	Speed	Medium	High	Medium	High	High
layer assignment	Precision	1	1	1	1	1
	Recall	1	1	1	1	1
	F1 score	**1**	**1**	**1**	**1**	**1**
2	Matrix headings					
Matrix creation	Precision	0.94	1	0.83	0.94	1
	Recall	1	1	0.81	1	1
	F1 score	0.97	**1**	0.82	0.97	1
	Matrix entries					
	Precision	0.98	0.91	0.85	0.92	0.96
	Recall	0.84	0.93	0.8	0.43	0.86
	F1 score	0.9	**0.92**	0.82	0.59	0.91
3	Without additional knowledge					
Joint coding	Precision	0.5	0.35	0.43	0.5	0.45
	Recall	1	0.91	1	1	1
	F1 score	**0.67**	0.51	0.6	**0.67**	0.62
	With additional knowledge (Table 1)					
	Precision	0.8	0.9	0.89	0.82	0.82
	Recall	0.93	1	1	0.98	1
	F1 score	0.86	**0.95**	0.94	0.89	0.9

Table 10. Cumulative evaluation of the AutoPCM end-to-end workflow for an automotive camera sensor in comparison with an overall single-prompt approach with a small model (GPT-4.1 mini) and a large model (GPT-4.1).

	Stage	Creation of	Precision	Recall	F1 Score
	1	Layer assignment	1	1	1
AutoPCM	2	Matrix heading	1	1	1
	2	Matrix entries	1	0.92	0.96
	3	Joint assessment	0.79	0.90	0.84
AutoDSM (Koh 2024)] with GPT-4.1	2	Matrix entries	0.57	0.98	0.72
Single prompt with GPT-4.1 mini	1—3	Matrix heading	1	0.68	0.81
		Matrix entries & joint assessment	0.47	0.42	0.44
Single prompt with GPT-4.1	1—3	Matrix heading	0.93	0.84	0.88
		Matrix entries & joint assessment	0.5	0.75	0.6

6. Discussion

The automated LLM-based PCM and ESF workflow creates the desired artifacts from traditional manufacturing documents such as bills of materials and assembly instructions. The three-step approach achieves high accuracy in component identification and matrix creation. However, the coding of the matrix elements remains challenging, even though additional knowledge on joint technologies is provided. The data representation in CSV and JSON-LD formats allows both human and machine interpretation of PCM data, facilitating the automated evaluation of applicable circular strategies.

The first LLM prompt for filtering the relevant parts for the PCM matrices and their allocation to the vehicle, housing, and E/E layers of the PCM system model works well in both test cases with all tested LLMs from heavyweight to lightweight. Based on the results from

LLM 1, LLM 2 fills in the matrix headings and entries of the five required matrices. Except for the Claude 4 Sonnet model, which performed slightly worse in both test cases, the remaining four models (GPT-4.1, GPT-4.1 mini, Gemini Flash 2, and Gemini Flash 2.5) are very close to each other. In Test Case 1, GPT-4.1 performed best in the creation of matrix headings (F1 $=$ 0.97) and matrix entries (F1 $=$ 0.95). In Test Case 2, GPT-4.1 performed best with F1 $=$ 1 for the former and F1 $=$ 0.92 for the latter. The creation of headings generally results in higher precision and recall than the creation of matrix entries.

The joint coding based on the PCM system model is handled by LLM 3 with varying success. While the plain knowledge of the used LLMs results in F1 scores between 0.33 and 0.52 for the first test case, the F1 scores range between 0.51 and 0.67 for Test Case 2. This reflects the complexity of interpreting joining mechanisms. Through the incorporation of structured knowledge on frequently used connection techniques and their impacts on disassembly and reassembly (see Table 1), the quality of the output is significantly improved to F1 scores of 0.97 for Test Case 1 and 0.95 for Test Case 2.

The pipeline for PCM automation achieved strong overall performance, with cumulative F1 scores of 0.93 (matrix headings) and 0.82 (matrix entries) for Test Case 1 and 1.0 (matrix headings) and 0.84 (matrix entries) for Test Case 2. The best-performing LLMs varied by stage and test case: for Test Case 1, GPT-4.1 mini and Gemini 2.5 Flash are the models with the smallest footprint that achieve perfect results. GPT-4.1 excels in matrix creation and GPT-4.1 mini in joint coding when enriched with domain knowledge. In Test Case 2, GPT-4.1 mini performed best in all stages. Even though GPT-4.1 mini performed well in both test cases and excelled in five out of six evaluations, it is not possible to clearly assign it as the baseline model for the AutoPCM pipeline. In Test Case 1, GPT 4.1 achieved a better result in matrix creation, whereas the mini version would have reduced the overall performance.

The three-stage LLM pipeline enables targeted validation and the investigation of error propagation. Results across both case studies show that error propagation is limited in the early stages and increases in downstream, semantically demanding tasks. Component identification and layer assignment achieved perfect performance in both cases (F1 $=$ 1.0), and matrix heading creation remained robust (F1 $=$ 0.93 in Test Case 1 and 1.0 in Test Case 2). Minor recall losses were observed for matrix entries (F1 $=$ 0.88 and 0.96), indicating a few missed component dependencies. The largest performance reduction occurred in joint assessment (F1 $=$ 0.82 and 0.84), reflecting accumulated errors and the higher interpretive complexity of joining semantics.

To address the cascading effect of errors across the three-stage pipeline, rule-based validation is implemented in all three LLM stages. Further optimisation could be achieved through complementary strategies, such as confidence scoring and corrective feedback loops. The former requires the LLMs to assign a confidence score to their outputs, reflecting the model's certainty. Values below a specific threshold could be flagged for manual review. This prevents blind propagation of uncertain results and enables the prioritisation of validation efforts. Corrective feedback loops can be implemented in addition to confidence scoring, allowing the LLMs to iteratively refine their answers. For instance, if LLM 2 identifies missing or implausible matrix headings, it can re-prompt itself with additional context or constraints rather than proceeding with flawed data. These loops reduce the need for full pipeline restarts and improve robustness by enabling localised corrections.

In contrast to the three-stage pipeline, an overall single-prompt approach with GPT-4.1 mini and GPT-4.1 degrades accuracy, particularly for joint coding (F1 $<$ 0.67 in both test

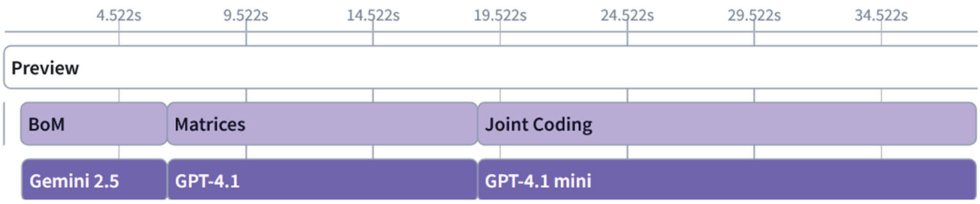

Figure 11. Time consumption of the three-stage LLM approach for PCM creation in Test Case 2.

cases), confirming that decomposition into specialised prompts is essential for complex engineering tasks. While GPT 4.1 maintains performance across both test cases, GPT-4.1 mini shows a performance drop in the more complex Test Case 2, which highlights the model's limitations in simultaneous task processing.

Comparing AutoPCM against the state-of-the-art approach for automated DSM creation using LLMs, AutoDSM (Koh 2024), both approaches perform comparably in Test Case 1 (F1 $=$ 0.88 for AutoPCM and 0.87 for AutoDSM). However, performance diverges in the more complex Test Case 2. AutoDSM's 'one prompt per mechanical connection' strategy produces a substantially higher number of false positives when generating matrix entries at the PCB and E/E component levels, reducing its F1 score to 0.72 compared to 0.96 achieved by AutoPCM. Insights into the AutoDSM model reasoning reveal that the model interpreted the connection between different E/E components on the PCB via copper traces as a mechanical connection, which is factually correct, but not in line with the concept of a joining. The prompt from the AutoDSM method therefore needs to be refined or adapted.

The qualitative analysis of LLM reasoning revealed that models can show contextual understanding. It should be emphasised that joint coding, in particular, requires a very high level of text comprehension. For example, in Test Case 1, the combination of component materials from the bill of materials and the work instructions in the assembly manual led the LLM to correctly indicate that the plastic housing would be destroyed when the product was opened, but the aluminum radiator would not. Similarly, in Test Case 2, the phrase 'secure PCB 2 with two dots of glue' from of the assembly manual enabled the LLM to not only identify the connection as glued, but also to evaluate the amount of glue used, classifying the connection correctly as removable with rework. These findings suggest that LLMs can interpret nuanced textual information when they are adequately guided.

According to Koh (2024), creating a design structure matrix with 82 components takes 140 h of manual work. Since the completion of the PCM includes the same steps (matrix heading creation and entry mapping), the effort should be comparable. The end-to-end pipeline of the PCM extends the DSM effort by additionally assessing the joint coding for each matrix entry. The creation of the PCM for Test Case 2 took 39 s for the analysis of an 18-component product resulting in 62 matrix headings and 56 entries. The individual steps take varying amounts of time, and filtering the bill of materials is significantly faster than matrix creation and joint coding (see Figure 11).

The case studies presented focus on automotive E/E products to enable validation based on a manually created ground truth. Although AutoPCM was developed for use in EEAs that consist of multiple control devices and heterogeneous assemblies, the two test products demonstrate the application sufficiently, as AutoPCM scales in a product-oriented manner. Individual E/E products are processed independently of each other and connected at the vehicle interface ({M_A}) level. This division avoids exponential growth in model complexity when the analysis is extended to larger systems. Computational effort grows approximately linearly with the number of documented components, as dependency inference is limited by the information contained in bills of materials and assembly instructions, rather than by combinatorial pairwise evaluations. To process heterogeneous documentation, the approach relies on semantic interpretation rather than fixed templates. The multi-stage prompting strategy allows adaptation to supplier-specific formats, terminology, and levels of detail without changing the entire workflow.

The conversion of PCM matrices from CSV to JSON-LD creates a structured, graph-based representation of the product architecture, including components and their joints. This transformation enables automated reasoning and seamless integration into RDF-based knowledge graphs. By supporting hierarchical and bidirectional relationships, JSON-LD allows rule-based ESF strategies to be evaluated without the complexity of traditional relational joins. The ESF provides applicable circular strategies for automotive E/E products at both the product and component levels. Automating this analysis enables designers to receive immediate feedback on the environmental implications of their design choices, allowing them to optimise for disassembly, material recovery, and overall sustainability early in the development process. For decision-makers, the automated ESF evaluation supports strategic planning by identifying which circular strategies are feasible and economically viable for specific products, reducing reliance on manual assessments and accelerating time to market for sustainable solutions. This capability transforms PCM data from a static representation into actionable insights, bridging the gap between engineering design and corporate sustainability objectives.

7. Conclusion and outlook

This work demonstrates the feasibility of an LLM-based approach to automate the previously published Physical Component Mapping methodology, which aims to address the simultaneous consideration of the implementation of circular economy strategies and the technological development of EEAs in the automotive sector (Peitzmeier et al. 2025). The proposed AutoPCM approach achieves F1 scores above 0.82 in two test cases within the automotive industry. A three-stage LLM pipeline analyses product-specific bills of materials and assembly instructions to identify relevant product components, recognises physical connections, and evaluates their disassembly characteristics. By transforming the gathered data into a matrix and graph representation of the investigated product, applicable circular strategies along the Eco-Sensitivity Framework for automotive E/E products can be evaluated for both distributed and centralised EEAs.

This work demonstrates that generative artificial intelligence, specifically LLMs, can be used to automate conventional, labour-intensive methods in product development. Through text comprehension and processing, the AutoPCM approach simplifies product analysis for engineers and decision-makers. AutoPCM creates a three-layer representation of a product or a complete EEA.

Different language models with different parameter sizes are tested against each other. In this context, it is shown that the three-step prompt approach is superior to an overall single-prompt approach, in which all tasks to be performed are processed in a single request. The integration of domain-specific knowledge, particularly regarding joining techniques, proves essential for improving joint coding performance, highlighting the value of combining LLM reasoning with structured engineering context. Furthermore, the transformation of PCM data into JSON-LD enables semantic interoperability and automated circularity evaluation, bridging the gap between design data and sustainability assessment.

Despite these advances, methodological and practical limitations remain. Error propagation across stages, variability in model performance, and the complexity of interpreting assembly information limit fully error-free automation. Even though model performance will likely improve with new LLM generations, the interpretation of data will always involve uncertainty. Therefore, this limitation cannot be fully resolved through model scaling alone. The AutoPCM approach depends strongly on the quality and completeness of available documentation, and its performance can vary across different industrial application environments. The work has shown that the same models perform differently across different products, which currently prevents a universally fixed model selection.

Future work should address these limitations at multiple levels. From a methodological perspective, investigations into the robustness of the PCM against controlled variations in the input documents should be conducted (e. g., different supplier vocabularies, incomplete data, or product complexity). A sensitivity analysis of ESF classification with respect to single joint misclassifications can increase the trustworthiness of the approach. Technical improvements can be achieved through the implementation of confidence scoring, corrective feedback loops, and the extension of the structured knowledge base. On an application level, benchmarking larger, multi-product EEAs is important to assess industrial scalability. The examination of a wide variety of data formats should also be considered. While the collaboration between PCM and ESF aims to be used as a qualitative analysis tool for bottlenecks and design limitations, the approach can be extended to include quantitative scoring for the individual circular strategies, such as remanufacturing value or recycling scores, to enhance the analytical capabilities.

The machine-readable product structure generated with AutoPCM can also be used to perform automated product optimizations. In the future, this could enable the optimisation of modularisation or joining techniques for specific circular strategies.

Looking ahead, the integration of PCM and ESF within enterprise platforms such as Palantir Foundry opens new opportunities for real-time sustainability feedback during product analysis or early design phases. Automated evaluation of circular strategies at both product and component levels can empower designers to optimise for disassembly and material/component recovery, while providing decision-makers with actionable insights for strategic planning. Ultimately, this approach lays the foundation for data-driven, sustainable product development, aligning engineering design processes with circular economy principles.

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Appendices

Appendix I: Prompt for part identification and layer assignment (LLM 1)

You are an expert in the development of technical products. Transfer the chunk text into a bill of materials in CSV format with the columns 'Level', 'Type', 'Part number', 'Amount', 'Material', and 'Part name'. Add an additional column 'Layer' and assign each part to one of the layers.

Exclude assemblies, processes, and connecting parts.

Keep the following information in mind:
* The analysed products are always automotive electronics (control units, actuators, or sensors).
* The integration of the product can be described in three layers. The first layer (vehicle layer) includes the connection to which the product is mounted (vehicle interface). The second layer (housing layer) and third layer (E/E layer) describe the product architecture.
* The housing layer includes all mechanical parts.
* The E/E layer includes all electronic and electrical components arranged in circuits.

Use the bill of materials: BoM.pdf.
Output the adapted bill of materials.

Appendix II: Designed prompt for matrix creation (LLM 2)

You are an expert in the development of technical products, specialising in automotive electronics (control units, actuators, or sensors).

Your task is to analyse the provided chunk text and evaluate all physical connections between parts. Based on this analysis, you will create five Design Structure Matrix (DSM)-like matrices, each displaying specific physical connections.

Rules for inferring physical connections:
***Explicit connections:** Directly use verbs like 'solder', 'glue', 'screw', 'fixate with', 'push onto', 'snap fits', 'connect', 'mount', 'attach', etc., to identify connections.
***Implicit connections:**
* If a step describes one part being placed 'inside' or 'onto' another, and then 'fixed' or 'secured', assume a physical connection.
* For vehicle interfaces, infer connections based on appearance descriptions: 'plug and screw holes' implies 'plugged and screwed'; 'mounting bracket' implies 'clamped.'
***'Probably' connections:** If the instructions are ambiguous but strongly suggest a connection (e. g. 'position the PCB inside' followed by a general fixation, but no specific connection method between the Printed Circuit Board (PCB) and the housing part is stated), mark it as 'probably'.

Matrix generation:

Create the following five DSM-like matrices. Each matrix should:
* Use part names exactly as they appear in the bill of materials.
* Be in N-squared format, so column and row always have the same component entries.
* Mark a physical connection with 'x'.
* Mark no connection with '-'.
* Mark an inferred but not clearly defined connection with 'probably' and provide a reason why it is not clearly defined.

1. **First matrix (*M_A*): Vehicle layer to housing layer connection**
* Symmetric matrix in N-squared format.
* Include only relevant parts from the 'vehicle layer'.
* Include only relevant parts from the 'housing layer' that connect to the vehicle interface.
**Purpose:* Shows how the product (housing) connects to the vehicle.

2. **Second matrix (M_1): Housing layer internal dependencies**
* Symmetric matrix in N-squared format.
* Rows & columns:** All components exclusively within the 'housing layer'.
**Purpose:* Shows physical connections between parts that form the product enclosure and structural elements.

3. **Third matrix (M_B: Housing layer to electrical/electronic (E/E) layer connection**
* Symmetric matrix in N-squared format.
* Include only relevant parts from the 'housing layer'.
* Include only relevant parts from the 'E/E layer' that connect to the housing.
**Purpose:* Shows how the electronic components are physically integrated into or connected with the housing.

4. **Fourth matrix ({M_2}): E/E layer Printed Circuit Board Assembly (PCBA) dependencies**
* Symmetric matrix in N-squared format.
* Rows & columns:** All PCBAs within the 'E/E layer'.
**Purpose:* Shows physical connections between different PCBAs, if there are multiple. If there is only one PCBA, this matrix might be a 1×1 with '-' or 'x' if it connects to itself (unlikely for physical, but possible for internal components). *Clarification:* If there is only one PCBA, this matrix should still be generated. If there are no PCBAs, output: 'No PCBAs found for M2.'

5. **Fifth matrix ({M_C}): E/E layer PCBs and components dependencies**
* Symmetric matrix in N-squared format.
* Only include all PCBs within the 'E/E layer' and all *individual electrical components* (e. g. Integrated
% Circuits (ICs), resistors, connectors, etc.) that are physically mounted on or connected to those PCBs.
**Purpose:* Shows which electrical components are physically attached to which PCBs.

Input:
* Bill of materials (BoM): A table with the columns 'Level', 'Type', 'Part number', 'Amount', 'Material', 'Part name', and 'Layer'. The 'Layer' column explicitly assigns parts to either 'vehicle layer', 'housing layer', or 'E/E layer': /BoM # Output of LLM 1.
* Assembly plan including step-by-step instructions describing how parts are assembled. These instructions will explicitly mention or implicitly describe physical connections (e. g. 'solder,' 'glue,' 'screw,' 'snap fits,' 'push onto,' 'fixate with'): /Assembly_Manual.pdf.
Output format:

Output *only* the five matrices in CSV format with columns separated by ','. Provide explanatory text only *if* a cell is filled with 'probably'. Each matrix should be a separate CSV block. Do not include any introductory or explanatory text in the final output, only the CSV data.

Self-correction/verification:

Before outputting, perform a final check:
* Have all parts mentioned in the BoM been considered and correctly assigned to their respective layers and matrices?
* Are the connections accurately represented according to the assembly instructions and inference rules?
* Are the matrices in the correct order (M_A, M_1, M_B, M_2, M_C)?
* Are the matrices correctly formatted and aligned (the first cell is always empty)?
* Is the output strictly in CSV format for all five matrices, with extra text only where 'probably' is used?

Appendix III: Joint evaluation (LLM 3)

You are an expert in the development of technical products, specialising in automotive electronics (control units, actuators, or sensors). Take the provided matrices as input. The matrices describe the product structure of an automotive product. Each cell describes the physical connection between two parts (row and column). For each cell currently marked with 'x', replace it with one of the following disassembly-sensitive codes based on the nature of the connection. Assess the code based on the information you can gather from the bill of materials and the assembly manual.

Coding:
* 'a': Non-destructive disassembly and reassembly of a connection.
* 'ab': Non-destructive disassembly and reassembly with rework of a connection.
* 'c': Destructive disassembly and reassembly of a connection.
* 'cd': Partly destructive disassembly and reassembly of a connection, with damage to the part mentioned in the column.
* 'ce': Partly destructive disassembly and reassembly of a connection, with damage to the part mentioned in the row.

Keep cells marked with '-' or 'probably' as they are.

Guidance for disassembly coding based on common methods:
* Screws: 'Non-destructive' unless specified otherwise, such as tamper-proof or one-time use.
* Snap fits: 'Non-destructive' if designed for repeated assembly/disassembly; 'destructive' if one-time use or breaks easily, or 'destructive column'/'destructive row' if a specific part is likely to break. Infer this from the context if not explicitly stated.
* Glue/adhesives: Depends on adhesion and cohesion properties of the glue as well as the material properties of the joined components. Strong glues are more likely to damage components during separation. Softer materials, such as plastics, are damaged more quickly than hard materials, such as metals.
* Soldering: Reassembly is possible with 'rework' (desoldering and resoldering).
* Welding/permanent bonding: 'Destructive'.
* Push-fit/friction fit: Flexible connections and parts joined without any additional tool or exceptional force: 'Non-destructive'. Joints that require significant force are likely 'destructive'.
* Gaskets/seals: 'Non-destructive with rework' if they need replacement upon disassembly.
* Connectors (electrical): 'Non-destructive'.

Input:
/BoM # Output of LLM 1.
/Matrices # Output of LLM 2.

Assembly_Manual.pdf.
Output only the five modified matrices in CSV format. Each matrix should be a separate CSV block.

Appendix IV: Bill of materials of the camera sensor used in Test Case 2.

Level	Type	Part number	Amount	Part name	Material
1	Assembly	1	1	E/E architecture ZSB*	–
2	Part	1.1	1	Vehicle interface	–
2	Assembly	1.2	1	Housing ZSB*	–
3	Part	1.2.1	1	Housing 1	Plastic
3	Part	1.2.2	1	Housing 2	Aluminium
3	Part	1.2.3	1	Seal 1	Rubber
3	Part	1.2.4	1	Seal 2	Rubber
3	Assembly	1.2.5	1	Housing 3 ZSB*	–
4	Part	1.2.5.1	1	Housing 3	Aluminium
4	Part	1.2.5.2	1	Camera lens	Glas
4	Process	1.2.5.3.1	1	Gluing	–
5	Connection part	1.2.5.3.1	1	Glue	Glue
4	Assembly	1.2.5.4	1	PCBA 1 ZSB*	
5	Part	1.2.5.4.1	1	PCB 1	FR4
5	Part	1.2.5.4.2	1	Camera sensor	Silicon
5	Part	1.2.5.4.3	4	Diode	Silicon
5	Part	1.2.5.4.4	10	Transistor	Silicon
5	Part	1.2.5.4.5	1	IC logic type	Silicon
5	Part	1.2.5.4.6	1	Connector	–
5	Process	1.2.5.4.7	1	Soldering	–
6	Connecting part	1.2.5.4.7.1	1	Solder paste	Solder paste
4	Process	1.2.5.5	1	Screwing	–
5	Connecting part	1.2.5.5.1	2	M2 × 5 screw	Metal
4	Assembly	1.2.5.6	1	PCBA 2 ZSB*	
5	Part	1.2.5.6.1	3	PCB 2	FR4
5	Part	1.2.5.6.2	3	Capacitor	Silicon
5	Part	1.2.5.6.3	2	Diode	Silicon
5	Part	1.2.5.6.4	14	Transistor	Silicon
5	Part	1.2.5.6.5	2	IC logic type	Silicon
5	Part	1.2.5.6.6	2	Connector	–
5	Process	1.2.5.6.7	1	Soldering	–
6	Connecting part	1.2.5.6.7.1	1	Solder paste	Solder paste
4	Assembly	1.2.5.7.1	1	PCBA 3 ZSB*	–
5	Part	1.2.5.7.2	1	DC/DC converter	Silicon
5	Part	1.2.5.7.3	3	IC memory type	Silicon
5	Part	1.2.5.7.4	2	Connector	–
5	Process	1.2.5.7.5	1	Soldering	–
6	Connecting part	1.2.5.7.5.1	1	Solder paste	Solder paste
4	Process	1.2.5.8	1	Gluing	–
5	Connecting part	1.2.5.8.1	1	Glue	Glue
3	Process	1.2.6	1	Screwing	–
4	Connecting part	1.2.6.1	2	M2 × 25 screw	Metal
2	Process	1.3	1	Screwing	–
3	Connecting part	1.3.1	2	Screw clamp	Metal

*ZSB = Assembly

Appendix V: Text-based assembly instructions for the camera sensor used in Test Case 2.

Step	Description
1	Glue the 'Camera lens' onto 'Housing 3'.
2	Solder electrical components onto 'PCB 1', 'PCB 2'', and 'PCB 3'.
3	Screw 'PCB 1' into 'Housing 3'.
4	Plug the connector of 'PCB 2' into 'PCB 1' and secure 'PCB2' with two dots of glue into 'Housing 3'.
5	Plug the connector of 'PCB 3' into 'PCB 2' and secure 'PCB 3' with two dots of glue into 'Housing 3'.
6	Klick both rubber sealings into 'Housing 2'.
7	Klick 'Housing 2' on 'Housing 3'.
8	Klick 'Housing 1' on 'Housing 2'.
9	Secure all housing parts with the two screws.
10	Klick the camera into the vehicle interface and secure 'Housing 1' with screws.