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AI Integration in Automotive Packaging Engineering for Multi-Constraint Component Optimization

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Abstract

This paper introduces a framework for the packaging of components in a vehicle's three-dimensional structure that is grounded in evidence and reproducible when taking advantage of the potential of artificial intelligence (AI) tools. The public OSU–Honda CarHoods10k dataset provides over 10,000 3D hood-frame designs based on 109 parameterized designs, along with design parameters and finite element (FE) performance data. The data package is about 45.66 GB, including design parameters and finite-element (FE) performance data. This dataset is not a multi-component vehicle-layout dataset and can't be used for a complete validation of a vehicle packaging optimizer: thermal, service access, or assembly data of the vehicle are not available at the component level. The studies of published adjacent work have shown that an improved solution with 3 times less computational budget could be offered, a result specific to this study but not predicted for automotive packaging. The proposed framework formalizes the placement variables, geometric constraints, engineering constraints, a model of screening by an artificial neural network (ANN), and a genetic search by NSGA-II, where the two objectives change. It also defines a controlled validation protocol to manual and rule-based baselines. There are no new vehicle-program performance gains since no proprietary vehicle-program layout dataset, executable code, or experimental logs for auditing were provided. The applicable vehicle-program specifications and relevant standards should supply acceptance limits.

Keywords: Artificial Intelligence, Machine Learning, Automotive Packaging, Optimization, Genetic Algorithms

1. Introduction

AI and ML engineers can aid in engineering design, for example, by making performance predictions, filtering, and optimizing a candidate design solution. The packaging of a vehicle is the positioning and direction of elements inside a vehicle architecture, not the activities of packaging products shipped in the field or to the consumer. Resources for automotive geometry are publicly available, and studies have been published that can give a good starting point for modelling the system-level components; however, these should be distinguished from vehicle-layout optimization. Availability information for multiobject placement information, service-access envelopes, thermal and vibration labels, and assembly constraints for a complete vehicle packaging system is not guaranteed by component geometry information.

Automotive parts packing is a constrained 3-D packaging problem. Each component is required to stay within its allowable installation envelope, has defined clearances from other adjacent components/vehicle structures, and is installed properly to the mounting interfaces while maintaining enough clearance for assembly, inspection, and maintenance. Additional engineering verification may be required for aspects of thermal, vibration, environmental, manufacturability, and interface compatibility based on the function of the component and its location. The applicable environmental-testing requirements should be chosen for the type of component and its installation. These standards do not call for a threshold, or limit, or acceptance of a universal nature for any vehicle system, any part of any vehicle, or any grade or level for any vehicle; instead, the vehicle-program specifications and the engineering specifications are controlling.

Feasibility prediction and optimization through AI can lower the number of candidate layouts that must undergo a "computer-aided engineering (CAE)" analysis, a computationally intensive approach. However, it relies on the availability of training data to represent data faithfully and to be accurately labelled and, critically, to control for false-feasible predictions. Previous studies on automatic powertrain placement and geometry modelling of the individual components have shown that applicable optimization and modelling techniques can be studied independently. The developments themselves are not, however, sufficient proof that an artificial neural network–genetic algorithm (ANN–GA) workflow has led to a certain reduction of design time, cost, mass or packaging space for a complete vehicle layout. Hence, such falsifiable optimization activities, and the associated protocol for their evaluation, are suggested in the present work not as actual experimental performance comparisons. In the present work, therefore, the actual results of the performance comparisons are not presented, but the proposed optimization activities are testable, as well as the suggested protocol for the evaluation of the optimization activities.

Four main contributions of this paper include the formulation of the automotive component placement problem in three dimensions and multi-constraints; identification of publicly available component-level geometry data and geometry data of the vehicle layout needed for full system validation; a three-stage solution comprising an ANN-based feasibility screening stage and an NSGA-II search when multiple objectives are considered; and the definition of an auditable evaluation protocol that includes geometric feasibility checks, independent CAE validation, computational runtime, and engineering trade-offs. The framework is designed to support practical investigation in the context of automotive engineering workflows. Although it does not define any new measurable improvements without any evidence of its implementation and any experimental proof of it.

2. Literature review

Automotive packaging optimization combines three-dimensional component placement, geometric constraint handling, and engineering performance evaluation. Research in automated vehicle packaging, spatial powertrain placement, and integrated component-layout optimization provides a foundation for developing computational methods for these tasks. However, component-level design optimization and complete vehicle packaging are different problems: improving an individual component does not necessarily produce a feasible arrangement of multiple components within a shared vehicle envelope.

2.1 AI/ML Methods in Engineering Design

Machine learning (ML) can support engineering optimization by approximating computationally expensive simulations, screening candidate designs, and identifying promising regions of a design space. Deep-learning methods have been integrated into computer-aided design and engineering workflows to generate and evaluate conceptual wheel designs (Yoo, Lee, Kim, Hwang, Park, & N. Kang, 2021). Automated machine learning combined with genetic algorithms has also been coupled with computational fluid dynamics for engine-design optimization (Owoyele, et al., 2022). Multi-objective structural optimization has been investigated for vehicle wheels, illustrating how competing engineering objectives can be assessed during preliminary design (Stabile, Ballo, Gobbi, & G. Previati, 2024). Deep-learning-assisted methods have further been developed to accelerate topology optimization (Padhi, Chakraborty, Chakrabarti, & R. Chowdhury, 2024).

These studies demonstrate the relevance of AI-assisted engineering design, but their findings must be interpreted within their respective applications. Wheel generation, engine-flow optimization, and topology optimization do not directly establish the feasibility or performance of an AI-based multi-component vehicle packaging system. For the present application, any surrogate model must be trained and tested using data representative of the target components, geometry, operating conditions, and engineering constraints.

Figure 1 illustrates a simplified workflow that uses AI and ML techniques to convert design-process inputs. Technologies such as Generative AI, machine learning, computer vision, and predictive simulation are used for various engineering applications such as concept generation, virtual prototyping, material selection, structural modeling, quality inspection, and predictive maintenance. Incorporating these applications can enhance design quality and performance, cut back on physical prototype use, and speed up the design process.

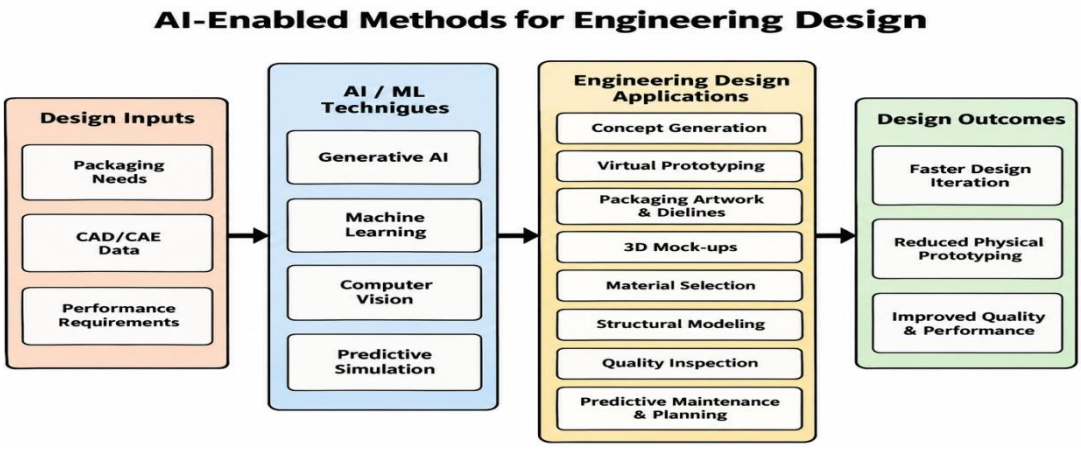


Figure 1: AI-enabled engineering design workflow.

2.2 AI-Driven Automotive Packaging and Component Placement

Automated vehicle packaging research has examined algorithmic placement using computer-aided design geometry (Sethuraman, et al., 2020). Related work has formulated spatial placement of vehicle powertrain components, including component orientations, relative positions, and alignment requirements, and demonstrated the method on a four-wheel-drive electric-vehicle configuration (Ponticelli, Farroni, Genovese, Dell'Annunziata, Timpone, & A. Sakhnevych, 2025). Integrated component-layout and structural-topology

optimization has also been investigated with interface-stress constraints. Collectively, these studies establish relevant approaches for representing placement decisions and incorporating engineering conditions into computational design.

The key to multi-component packaging lies in more than simply assembling packages so that the components will not collide. The layout should also include clearances, mounting interfaces and assembly considerations in accordance with specified requirements and easy access for services and interactions and all thermal and vibration requirements are applicable. These conditions are determined by the vehicle (machine) architecture and part function. As a result, an optimization framework needs to identify the universal geometric checks from vehicle-program-specific engineering rules (Kelmendi & G. Pappas, 2025)

2.3 CAD/CAE-Based Optimization

Computer aided design (CAD) provides component geometry, coordinate systems, mounting interfaces, and installation envelopes, while computer aided engineering (CAE) evaluates physical behavior to support optimization of candidate layouts (Wei, Vaze, & A. Jacquillat, 2020). Metamodels and transfer learning can improve optimization efficiency through knowledge reuse, but predictions require validation before design compliance can be confirmed (Colella, Lange, & F. Duddeck, 2024)

Figure 2 illustrates the iterative integration of AI, CAD, and CAE for automotive component packaging optimization. It demonstrates a process for candidate layouts, first to consider the engineering constraints, then incorporate the predictions of simulations to further improve the capability to meet engineering objectives of feasible, improved design quality, and engineering performance.

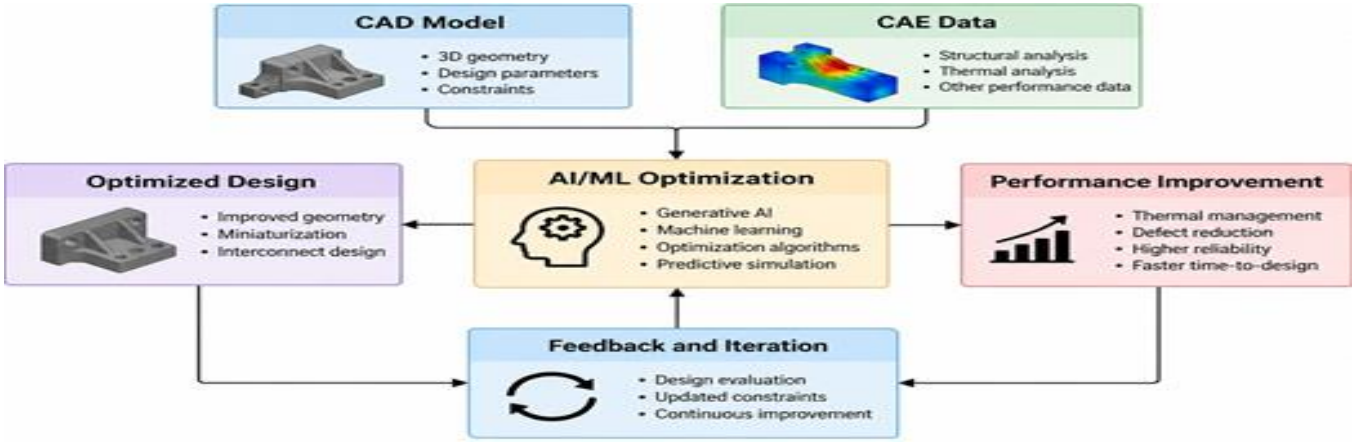


Figure 2: AI-integrated CAD/CAE optimization workflow with iterative engineering performance improvement

2. 4 Comparative Analysis and Research Gap

The surveyed studies reflect different complementary aspects of engineering optimization connected to algorithmic packaging of a vehicle, the placement of the powertrain, optimization of the layout of components, the component design using artificial intelligence, the surrogate modelling, and finally the optimization for assembly. Consistent and reliable performance of one integrated AI-based approach, however, would require that it successfully address all the geometric, thermal, vibration, serviceability, and assembly

constraints in a complete vehicle layout in general. Validating computational models is crucial when decisions in engineering are based on these models. Research on verification and validation of digital twins in manufacturing emphasizes the importance of establishing whether a computational representation is implemented correctly and whether its outputs adequately represent the intended physical system (G. Waters, 2025). Applied to automotive packaging, this principle requires explicit constraint checks, documented simulation settings, independent evaluation of shortlisted layouts, and comparison with defined baseline methods.

The principal research gap is therefore the lack of demonstrated evidence, within the scope of this study, for a reproducible AI-assisted workflow that integrates multi-component placement, explicit hard-constraint enforcement, surrogate screening, optimization, and independent CAD/CAE validation. Addressing this gap requires an authorized vehicle-layout dataset containing component geometry, mounting interfaces, packaging boundaries, required clearances, service-access regions, and relevant engineering-analysis results. Baseline layouts and experiment logs are also needed to evaluate whether the proposed method offers measurable practical benefits.

This study proposes a structured ANN-assisted optimization and validation framework rather than claiming experimentally proven industrial improvements. Its contribution is to define how candidate layouts can be generated, screened, checked, and compared reproducibly. Improvements in design time, packaging compactness, mass, or cost must be established through controlled experiments using the appropriate vehicle-specific data (Yuan, Jong, & W. D. van Driel, 2024).

Table 1 is a summary report of 10 related automotive packaging, artificial intelligence (AI) based design and engineering optimization related studies. It gives emphasis on their major contributions and limitations, highlighting the need for a research gap for integrated research for intelligent component placement, engineering constraints and on independent CAD/CAE validation.

Table 1: Comparative Review of AI-Assisted Automotive Packaging and Engineering Optimization

Research focus	Main contribution	Research gap
Automated vehicle packaging	Automates component placement.	Limited integrated constraint validation.
Powertrain placement	Optimizes component positions and orientations.	Focuses on a specific vehicle configuration.
Component layout	Combines layout and structural optimization.	Limited scope for full-vehicle packaging.
AI-assisted wheel design	Applies deep learning to engineering design.	Does not address multi-component placement.
Engine optimization	Combines machine learning and genetic algorithms.	Focuses on engine design.

Wheel optimization	Evaluates competing design objectives.	Does not optimize complete vehicle layouts.
Topology optimization	Uses deep learning to support structural optimization.	Different from spatial packaging.
Gearbox assembly	Uses metamodels to reduce computational effort.	Results are specific to gearbox design.
Crash-design optimization	Applies transfer learning.	Requires validation for new designs.
Manufacturing digital twins	Reviews model verification and validation.	Does not provide a packaging optimization method.

3. Problem statement

The automotive components package involves placement and orientation of parts in the 3-D space required within the vehicle, considering the geometric, functional, and manufacturing constraints. Improper mounting can result in interference among components, improper clearances, limited maintenance access, and thermal vibration issues. The central problem is to develop an AI-assisted optimization framework that generates compact, feasible component layouts while respecting vehicle-specific engineering constraints (Li, et al., 2026). Public geometry datasets can support component-level modelling, but complete vehicle validation requires additional CAD/CAE data, mounting interfaces, operating conditions, and service-access requirements.

3.1 Mathematical Formulation

The design variables comprise each component's three-dimensional position (xi,yi,zi), orientation (αi, βi,γi)and, where applicable, an approved component variant (Pappalardo, Magaldi, Masucci, Regina, & A. Naddeo, 2024). These variables are bounded by the available installation space, mounting locations, and vehicle-program specifications.

The framework considers three potential objectives. Layout compactness aims to minimize the overall bounding box volume enclosing the placed components. Assembly mass aims to minimize the total component mass when approved alternatives allow the mass to vary. Assembly cost aims to minimize component and layout dependent assembly costs when reliable cost data are available. The compactness measure compares the combined component volume with the bounding-box volume of the resulting layout. Because the component volumes remain fixed when only placement changes, this measure captures layout compactness rather than material occupancy of the entire vehicle. Mass and cost are not treated as variable objectives when component configurations and assembly costs remain fixed.

3.2 Engineering Constraints

Every candidate layout must satisfy the applicable constraints before it can be accepted. Geometric feasibility requires components to remain within the permitted packaging boundaries, avoid collisions, and maintain the specified clearances. Thermal and vibration

requirements require components to satisfy the limits established for their operating conditions and installation locations. Serviceability requires the necessary tool access, inspection space, and component removal paths to remain unobstructed. Mounting and assembly requirements require interfaces to align correctly and components to be installable in the required sequence. Applicable mass and cost limits must also be enforced where specified. Clearance values, thermal limits, vibration thresholds, and access requirements must be obtained from approved engineering specifications and validated analyses. These requirements must not be assumed to be universal across vehicle components.

3.3 AI-Assisted Optimization

An artificial neural network (ANN) can be used to filter the candidates and estimate the feasibility of candidate layouts, thereby reducing the number of candidates to be sent for more costly evaluation (Wang, Fu, Du, Gao, Huang, & Z. Liu, 2023). A GA can be used to conduct search on the design space, and use the NSGA-II when there are at least two objectives which are actual random. A single-objective optimiser will be more useful for a single changing objective. ANN predictions cannot be used as a substitute for the explicit geometric checks or independent computer-aided engineering (CAE) (validity) verifications. Selected candidate layouts will have to be compared with the actual engineering constraints, and all false-feasible predictions have to be documented during the assessment. Depending on the type of the component and installation conditions, relevant automotive environmental requirements, such as ISO 16750-1 and ISO 16750-4, can be used in determining applicable testing requirements for components.

3.4 Assumptions and Validation Requirements

The framework assumes that the geometry of the components, coordinate systems, applications of mounting interfaces, tolerances and necessary clearances and the relevant operating conditions and acceptance limits are available and clearly defined. Where vehicle-specific data are missing, the corresponding constraint must be reported as unvalidated. Claims of improved design time, mass, cost, or packaging performance require reproducible experiments against clearly defined baseline methods.

4. Methodology

4. 1 Research Framework and Reproducible Study Design

This study proposes a reproducible framework for AI-assisted automotive component packaging optimization. It does not report a completed industrial experiment. The methodology combines CAD geometry processing, deterministic constraint checking, artificial neural network (ANN) screening, evolutionary optimization, and independent computer-aided engineering (CAE) validation. Neural networks can approximate nonlinear relationships, while surrogate modelling can reduce the need for expensive engineering evaluations when the model is adequately trained and validated (Kudela & R. Matousek, 2022).

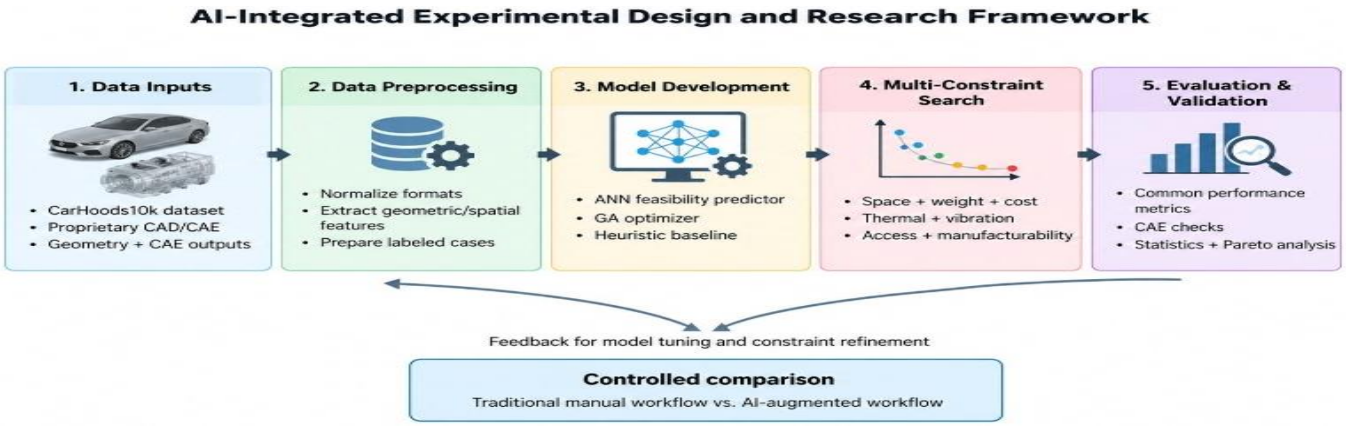


Figure 3: AI-integrated experimental design and research framework for automotive packaging optimization.

The workflow of the experiment was divided into five stages, as summarized in Figure 3. Stage 1 is the combination of CarHoods10k and proprietary CAD/CAE inputs which include assembly constraint, Geometry and thermal results. Stage 2 normalizes, extracts component features and spatial features and creates expert verified training samples. The feasibility predictor in ANN is trained in stage 3 and the baseline - GA and heuristic is configured; model settings for cross-validation are determined in stage 3. In stage 4, multi-objective search is performed while satisfying geometric, thermal, vibration, accessibility, weight and cost constraints. The feasibility of layouts is checked by considering packaging-density, constraint-violation, computational-time, downstream-CAE in stage 5. The designed stages are provided as a replicable foundation to compare the AI-assisted optimization process to the traditional process.

Experimental design principles can guide the selection of representative candidate layouts, while efficient global optimization provides a basis for managing expensive evaluations (Huang, Li, & X. Yao, 2020). Reproducibility requires recording data provenance, software versions, random seeds, constraint definitions, failed simulations, and optimization settings.

4.2 Data Acquisition and Preprocessing

The data strategy clearly keeps public industry geometry data separate from the packaging attributes of vehicles. A set of 109 base hood-frame mesh geometries is used to generate and save over 10,000 hood-frame mesh geometries (CarHoods10k) publicly in the Dryad repository. It has a published data requirement (D.P.) of ~ 45.66 GB, which contains design parameters and finite-element (F.E.) performance values. Although these data can be used for component-level geometry processing and exploration of the design space, they cannot be used to build a complete vehicle envelope or to design an envelope with labelled packaging layouts for the parts.

For a complete vehicle packing experiment, it is necessary to have authorized CAD/CAE information that includes component solids, mounting interfaces, allowed installation zones, clearances, element access zones, relevant operating conditions, etc., and basic layouts. Data should be documented for data authorization, anonymization, units, coordinate convention, component identifiers, and inclusion criteria. The data should be split by it being a related or near-duplicate answer, before that is split by base geometry, or vehicle program, to minimize the risk of having these either included in the training or the test set. A

70/15/15 training-validation-test split may be used if justified by the available sample size; it is a proposed protocol, not a reported experimental result

Table 2 summarizes three data sources supporting automotive packaging optimization: the CarHoods10k dataset, published electric vehicle powertrain placement studies, and authorized vehicle-program CAD/CAE data. It identifies their applications and limitations, emphasizing the need for proprietary engineering data and independent validation.

Table 2: Public Data Sources and Scope of Applicability

Data source	What it supports	Important limitation
CarHoods10k public dataset	Component level geometry processing and surrogate modelling	Does not provide a complete vehicle layout dataset.
Published EV powertrain placement study	Evidence that spatial placement and orientation can be modelled computationally	Does not validate the proposed ANN assisted workflow.
Authorized vehicle program CAD/CAE data	Full packaging constraints and independent engineering validation	Not supplied with this study; must be obtained and documented.

The public dataset's sample count and file size describe the released component dataset, not the number of vehicle-layout training examples. No proprietary sample count, feature count, or prediction accuracy is assumed

4.3 AI Model Architecture and Optimization Algorithm

The proposed ANN predicts whether a candidate layout is likely to satisfy explicitly labelled constraints (Choi, Nguyen, Sen, Udaykumar, & S. Baek, 2023). Inputs include component positions and orientations, with discrete variant variables included only when approved alternatives exist. Kriging and other metamodels are possible alternatives when the sample size is limited or simulation evaluations are expensive (Ayoob, Elahi, Zafar, Hamza, & Z. Wang, 2025). The optimization method depends on the objectives that can actually change. Single objective optimization is used when only one objective, such as layout compactness, varies. Multi objective optimization using NSGA II is used when two or more objectives vary and meaningful trade offs must be examined. Fixed mass or cost should be reported as attributes or treated as constraints rather than optimization objectives when the design variables cannot change them.

The ANN should NOT be used in place of the deterministic constraint checks. Its threshold should be based on validation data, paying special attention to false-feasible predictions (predictions that are feasible but fail the engineering requirements); Layouts will be independently checked with consistent CAD/CAE models, load cases, solver settings, and convergence criteria on all short-listed layouts. The test set is left untouched until the final testing and evaluation phase, and a set of hyperparameters should be determined from the training and validation sets. Reporting times, accuracy, hardware specifications, or the number of times the program was optimized may proceed only when applicable from an experimental logging record.

The proposed architecture is coupled between the CAD preprocessing and the deterministic constraint checking, and the ANN-based candidate screening and genetic optimization (Amirpour, Feng, & A. Entezari, 2026). Shortlisted solutions are then subjected to independent geometric and relevant CAE validation. When multiple objectives vary, NSGA-II retains a set of non-dominated solutions so that engineering trade-offs can be assessed rather than presenting one solution as universally optimal.

4.4 Evaluation Metrics and Comparative Analysis

Both the manual design and the two types of optimization, namely deterministic rule based optimization and ANN assisted optimization, are assessed based on the vehicle case, input design geometry, constraints, and validation protocol. The following measures are considered. Feasibility is evaluated based on the number and proportion of independently evaluated layouts that satisfy all applicable hard constraints. Geometric quality is assessed using minimum clearance margins and the number and types of geometric violations. Engineering compliance is evaluated based on thermal, vibration, service access, mounting, and assembly pass or fail results for applicable cases. Optimization quality is assessed using compactness and other valid objective values, including the non-dominated solutions identified after validation. Computational effort is evaluated based on the number of full CAD and CAE evaluations, elapsed computation time, and engineering hours required.

It is important to use a metric or checklist that has been documented, but is specific to the organization evaluated (no universal score should be assumed). After checking the assumptions, paired statistical tests might be applicable to the sample, if adequate independent and matched cases exist. Please submit this with effect size and confidence intervals, NOT just a p-value. It's too early to make a claim of statistical significance or improvement, as observations have not yet been made.

Table 3 outlines the evaluation protocol for automotive packaging optimization, covering test-case selection, comparison methods, data separation, constraint verification, performance reporting, and statistical analysis. It emphasizes consistent testing procedures, reliable feasibility assessment, transparent documentation, and statistically valid comparisons.

Table 3: Evaluation Protocol

Evaluation element	Required procedure
Test cases	Record vehicle preparations, accident and case numbers, and entry criteria.
Comparison methods	Apply manual, rule-based, and ANN-assisted techniques under the same constraints.
Data separation	Group geometries by base geometry or vehicle program before splitting the dataset.
Constraint verification	Record pass/fail results for each applicable engineering constraint.
Performance	Retain raw data on feasibility, objective values, runtime, and

reporting	engineering effort requirements.
Statistical analysis	Where the sample size supports valid comparisons, report effect sizes and confidence intervals.

Table 4 presents key metrics for evaluating automotive packaging optimization, including feasibility, compactness, mass, cost, design-cycle time, ANN performance, and optimization quality. Specifically establishes the procedures and reporting of measurements to ensure consistent and valid technical measurement performances that are transparent and reproducible.

Table 4: Operational Definitions of Key Metrics

Metric	Definition and reporting requirement
Feasible-layout rate	Percentage of independently evaluated candidates that satisfy all hard engineering constraints.
Layout compactness	Ratio of component solid volume to the enclosing layout bounding-box volume. Report this value as a compactness proxy.
Mass	Total mass of selected components and brackets. Do not claim mass optimization if component masses are fixed.
Cost	Documented costs of components and layout-dependent assembly. Specify the cost baseline used for comparison.
Design-cycle time	Report computation time, CAE analysis time, and engineering review effort separately.
ANN performance	Report precision, recall, calibration, and false-feasible rate using grouped hold-out data.
Optimization quality	Report validated objective values and Pareto solutions, together with algorithm settings and results from independent runs.

The evaluation process is followed in four phases: Freezing the input geometry and requirements; Generating potential layouts employing each comparison method; Shortening the number of layouts to carry out thorough, consensus-driven CAE/CAD-based modeling and validation; and comparing the feasibility, objective values, simulation time, and engineering time. All heat evaluation shall be based on applied heat loads, boundary conditions, and limits for components in question. It is necessary to employ a suitable mounting condition, case of vibration, and acceptance criteria in vibration evaluation. All acceptance thresholds should be based on the appropriate vehicle-program requirements.

Figure 4 illustrates the proposed evaluation and validation protocol. It presents four stages: input preparation, candidate generation, independent CAD/CAE validation, and performance comparison. The framework evaluates feasibility, geometric quality, engineering compliance, optimization quality, and computational effort across methods.

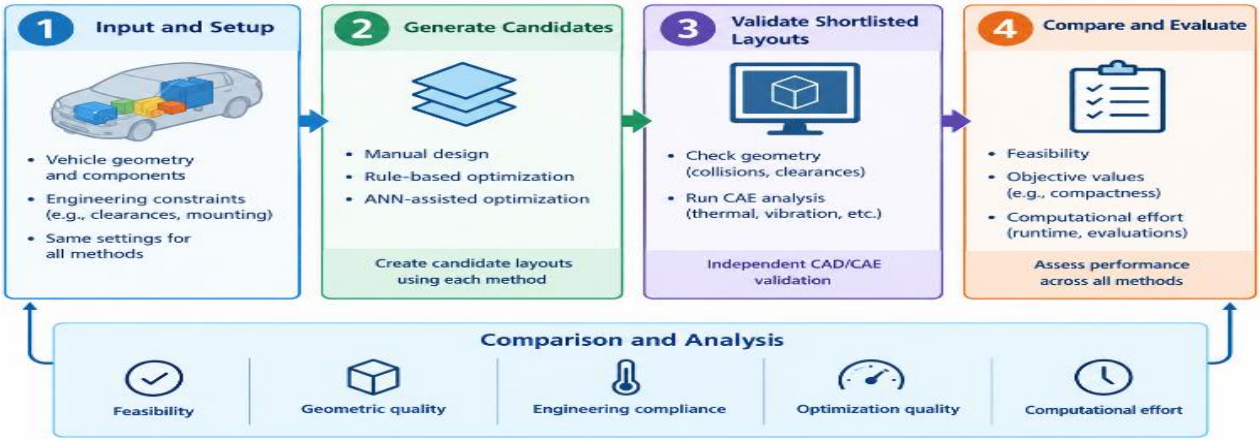


Figure 4: Proposed Comparative Evaluation and Validation Protocol

4.5 Methodological Limitations and Practical Requirements

The proposed framework cannot establish industrial performance improvements without an authorized multi-component vehicle dataset, a working implementation, and reproducible experimental records (Liu & T. Wang, 2025). The public component dataset alone cannot validate the complete packaging workflow. ANN predictions may also be unreliable for rare or previously unseen infeasible configurations, and simulation results require appropriate verification and validation before being treated as credible engineering evidence.

Table 5 summarizes six key limitations of the proposed framework and corresponding practical actions. It addresses incomplete packaging data, ANN misclassification, engineering requirements, implementation transparency, simulation uncertainty, and cross-platform generalization, outlining measures needed to improve reliability, reproducibility, and validation.

Table 2: Limitations and Required Follow-up

Limitation	Required action
Public data do not cover complete vehicle packaging	Obtain and document an authorized multi-component layout dataset.
ANN may misclassify infeasible layouts	Use grouped validation, track false-feasible predictions, and retain deterministic checks.
Thermal and vibration requirements are component-specific	Define load cases and acceptance criteria from engineering specifications.

No executed experiment is documented	Archive code, settings, seeds, candidate logs, and CAE results.
Simulation credibility is not automatic	Document verification, validation, and uncertainty assessment.
Generalization across vehicle platforms is unknown	Test on an independent vehicle program before making cross-platform claims.

5. Evidence, validation plan, and discussion

This chapter distinguishes verified published evidence from the proposed framework and the experiments that remain to be conducted. Because no authorized full-vehicle packaging dataset, executed optimization code, or experimental logs were available for this study, the results are presented as an evidence-based assessment and a reproducible validation plan rather than as completed industrial performance measurements.

5.1 Available Evidence and Dataset Boundary

The public OSU–Honda CarHoods10k dataset contains more than 10,000 three-dimensional hood-frame meshes derived from 109 parameterized base geometries. The dataset includes design parameters and finite-element performance values and is publicly available through Dryad. This dataset supports component-level geometry processing, design-space exploration, and investigation of predictive models. However, it is not a complete vehicle-layout dataset. It does not, by itself, provide the full vehicle envelope, multi-component placement labels, service-access regions, or all thermal and vibration information required to validate an integrated vehicle packaging optimizer.

A full-system evaluation therefore requires authorized vehicle-program data containing component geometry, mounting interfaces, packaging boundaries, required clearances, service-access volumes, applicable operating conditions, CAE results, and baseline layouts. The provenance, completeness, and permitted use of these data must be documented before experimentation.

Table 3: Reproducible Full-System Validation Protocol

Evaluation item	Required procedure	Evidence to record
Test cases	Select authorized vehicle assemblies and define independent cases.	Case identifiers, data source, inclusion criteria.
Methods compared	Compare manual, rule-based, and ANN-assisted optimization.	Baseline procedures, software versions, hardware.
Data separation	Group related geometries by base design or vehicle program before splitting.	Sample counts, grouping rules, split records.

Engineering constraints	Check envelope, collision, clearance, mounting, serviceability, and applicable thermal/vibration requirements.	Constraint-specific pass/fail results and failure logs.
Performance measures	Record feasibility, objective values, CAE evaluations, runtime, and engineering effort.	Raw observations and measurement definitions.
Statistical analysis	Use suitable comparisons for matched, independent cases.	Effect sizes, confidence intervals, assumptions, and exclusions.

Table 6 outlines a reproducible protocol for validating the proposed AI-assisted packaging framework. It sets rules for input data consistency, standard methods, and informational limits of engineering design, independent CAD/CAE checks, performance assessment, and reporting, to ensure that a fair comparison, reliability, and transparent assessment of both results and performance are possible.

5.2 Comparative Performance Analysis

There are no numerical comparisons of design time, layout _let_ness, mass reductions, cost savings, number of iterations, or ANN accuracy reported since the necessary paired observations and experiment logs are not available. These quantities are NOT to be estimated based on published literature or algorithm designs; they must be measured; they are not for use as inequalities that require solving. For a valid comparison, all of the vehicle geometry, engineering constraints, load cases, solver settings, and validation procedures must be identical for all methods. Evaluating the performance of the methods of manual design, deterministic rule-based optimization, and ANN-assisted optimization should be done on similar jobs, when possible. Immediate observations and the number of independent vehicle cases, number of full CAD/CAE evaluations, computational time, and engineering effort should be reported in the assessment. If sample size and experimental design permit, the results of comparisons should be accompanied by the confidence intervals and effect sizes. Verification and validation are different types of activities to determine the believability of computational engineering models (Jakeman, Barba, Martins, & T. O'Leary-Roseberry, 2026). For computational solid mechanics and general simulation models, there are additional practices for verification and for validation of numerical results that give further guidance for the evaluation of numerical results (C. J. Freitas, 2020). Global sensitivity analysis techniques can be used to help determine which uncertain inputs are influential (Iooss & P. Lemaître, 2015), and experimental-design techniques can be used to aid in planning for controlled comparisons. For simulation-based engineering work, computational fluid-dynamics verification, validation, and uncertainty quantification provide an additional documented reference for establishing simulation credibility (Mehta, Eklund, Romero, Pearce, & N. S. Keim, 2016).

Table 7 provides a definition of evaluation metrics for evaluating the proposed framework, which include feasibility, optimization quality, computational effort, and engineering performance. Sets uniform measurement criteria, computation methods, and reporting procedures to facilitate the transparent, reproducible, and fair comparison of optimization methods.

Table 4: Operational Definitions and Reporting Rules for Evaluation Metrics

Metric	Operational definition	Reporting requirement
Feasible-layout rate	Proportion of independently evaluated candidates passing all hard constraints.	Report the numerator, denominator, and constraint-specific failures.
Layout compactness	Total component solid volume divided by the enclosing layout bounding-box volume.	Keep the coordinate frame and calculation consistent; identify it as a compactness proxy.
Mass	Total mass of the selected components and brackets.	Report as constant if the component configurations are fixed.
Cost	Documented component costs and layout-dependent assembly costs.	Use a defined baseline and verified cost data.
Design-cycle time	Time required for comparable engineering tasks.	Separate computation, CAE execution, and engineering review.
ANN performance	Predictive performance on independent, grouped test data.	Report precision, recall, calibration, class balance, and false-feasible rate.
Optimization quality	Objective values and feasibility of candidate or Pareto solutions.	Report algorithm settings, stopping rules, random seeds, and independent runs.

5.3 Algorithm and Surrogate Reporting Requirements

Because the executable implementation and run logs were unavailable, candidate throughput, hardware utilization, runtime, generation count, and surrogate accuracy could not be reported. Reproducibility requires documenting hardware and software configurations, algorithm parameters, independent runs, stopping criteria, evaluation counts, and random seeds (Weise & Z. Wu, 2023). Surrogate reporting should include training-set composition, class balance, validation procedures, decision thresholds, and independent test results, particularly precision, recall, and false-feasible rates. A false-feasible prediction occurs when

the ANN classifies a candidate as compliant despite its failure to satisfy an engineering constraint. Such errors can be concealed by high overall accuracy; therefore, every candidate must undergo authoritative engineering constraint verification before acceptance.

5.4 Discussion and Limitations

The reason given for using AI-backed screening is that a predictive model could potentially help to screen candidates and avoid costly tests that might otherwise be conducted but are not necessary. The amount of any benefit, however, has not been measured in this work. Whether the proposed workflow can (or should) give any benefit to the design cycle time, size, or any other criteria must be verified in practice with properly defined benchmarks.

The limitations of the study include the scope of the available data, as some public geometry data are available for investigating individual components, but these data do not indicate the packaging feasibility of complete vehicles. The reliability of the surrogate model is also limited because the ANN may fail to classify layouts that are not feasible, particularly when working with a small number of examples or layouts that have not been previously observed. In addition, vehicle specific requirements involving thermal conditions, vibration, mounting, tooling access, clearance, and service constraints vary between vehicle designs. The credibility of the simulation results is another limitation, as CAE outputs need to be verified and validated, with associated uncertainties properly determined. Finally, generalization across different vehicle architectures cannot be guaranteed, as the findings from one vehicle architecture may not directly apply to another.

Deterministic constraint checker and final CAD/CAE validation must be authoritative. Independent evaluation should be done when transferring to another vehicle platform, as geometry, mounting points, and operating conditions, as well as engineering requirements, may differ. For reported results sensitive to uncertain inputs, sensitivity analysis should be employed to examine and determine if the reported results are materially sensitive to an uncertain input. The framework needs to be seen as a proposed methodology and not as a proven industrial solution, until these checks are concluded.

Table 8 highlights the main weaknesses of the framework and actions to be taken in implementing it in practice. It tackles issues related to data availability, the reliability of the surrogate model, engineering considerations, computing needs, uncertainty in the simulations, and the ability to generalize, and proposes strategies to improve the feasibility, reproducibility, transparency, and confidence in any future use of automotive packaging applications.

Table 8: Limitations and Practical Validation Actions

Limitation	Practical validation action
Public datasets do not represent complete vehicle packaging.	Obtain and document an authorized, multi-component vehicle-layout dataset.
ANN predictions may be incorrect.	Use grouped validation, monitor false-feasible predictions, and retain deterministic constraint checks.
Thermal and vibration	Define applicable load cases and acceptance

requirements vary by component.	limits using engineering specifications.
No experimental implementation is documented.	Archive source code, configurations, random seeds, candidate logs, and CAE results.
Simulation results may contain uncertainty.	Document verification, validation, and relevant uncertainty assessments.
Cross-platform performance is unknown.	Validate the approach on a second independent vehicle program before claiming generalizability.

6. Conclusion & future work

This study presents an evidence-grounded framework for integrating artificial intelligence (AI) into automotive component packaging engineering. The framework takes into account geometric compatibility, collision avoidance, clearance, mounting interfaces, and assembly access, along with other thermal and vibration constraints that apply to the placement of components in a vehicle's three-dimensional structure, and explores serviceability. It integrates a candidate screening system based on an artificial neural network (ANN), genetic optimization, and independent computer-aided design and engineering (CAD/CAE) verification to facilitate systematic searching for allowable package configuration solutions.

A key contribution is the distinction between component-level design optimization and complete vehicle-level packaging optimization. The OSU–Honda CarHoods10k data set is representative of both geometry and FE performance of the parts, which is great for component modelling, but is not sufficient to prove the feasibility of a complete multi-component vehicle layout. Consequently, the proposed framework treats this dataset as a potential resource for component-level model development rather than sufficient evidence of full-vehicle packaging performance. The framework also establishes a reproducible validation approach in which AI-assisted optimization is compared with manual and rule-based methods under consistent engineering constraints and computational conditions. All candidate answers require independent checking to be accepted as plausible, which entails geometric and engineering checks. In the case where multiple objectives really vary, there could be use of a multi-objective method like Non-dominated Sorting Genetic Algorithm II (NSGA-II); otherwise, the optimization method should follow the actual objective structure of the problem. Measures of performance should be well defined, such as constraint violations, feasible-solution rate, computational effort, and solution quality.

The most significant drawback is the fact that the framework introduced has not been tested with an auditable, full vehicle dataset; an executable implementation; and documented measurement outcomes. So, it is not claimed that the design time is improved, packaging efficiency or vehicle mass, cost or optimization accuracy is improved quantitatively. These improvements need to be shown to result from controlled experiments and independently verifiable results, and NOT predicted from neighboring experiments and/or on an artefact-by-artefact approach. Going forward, it is recommended to collect or create more representative vehicle-level geometry and constraint information, as well as apply the entire optimization process and verify it for various packaging scenarios. Several research directions are suggested as potential follow-on work: Testing the reliability of the surrogate model, testing model generalization to unseen configurations, computer-assisted engineering input

uncertainty, and computational trade-offs between AI-aided search and traditional optimization. In addition, automotive engineering collaboration would enable the addition of program-specific requirements in manufacturing, assembly, access to services, thermal considerations, and safety/illness and mechanical protection.

AI represents a promising tool for assisting next-generation packaging in the automotive industry by speeding up the process of evaluating candidates and aiding engineers to explore complex design spaces. However, if the data is unreliable, the engineering requirements are ambiguous, there is no independent validation, and there is no transparency regarding the report, then this doesn't really have any practical value. The proposed framework offers a structure by which the process can be implemented and evaluated in the future and also acknowledges that measurable benefits need to be shown, as that will be considered a validation of the approach for production-level automotive packaging.

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