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A Framework for the Selection of AI-based Methods to Support the Development of Passive Vehicle Safety Systems

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Abstract: The complexity of new products driven by rising requirements for new generations demands efficient development processes. A pronounced emphasis on artificial intelligence has resulted in a substantial array of methods in multiple application fields. Hence, this work proposes a framework for the systematic categorization and selection of artificial intelligence-based methods enabling the engineers to employ the best method at the best time. The framework is built upon the problem-solving cycle, discussed along, and verified within the industry use case of passive vehicle safety system design.

Keywords: Design Methodology, Artificial Intelligence (AI), Process Improvement, Virtual Engineering (VE)

1 Introduction

Contemporary trends in product development are characterized by numerous factors, with a growing emphasis on innovation and rapid technological advancements (Berisha and Lobov, 2021). These trends are driven not only by evolving customer requirements but also by legal regulations and changes precipitated by climate change (Schweitzer et al., 2023). In response to this highly dynamic environment, there is a growing need for efficient development processes guaranteeing technical and economic feasibility of more and more complex future product generations. In this context, the integration of emerging technologies, such as artificial intelligence (AI), in in the development processes and the products themselves is becoming more prevalent offering a variety of optimization potentials.

In the development of new vehicle generations, the best possible protection safety of road users within crash scenarios is given a high priority since road traffic injuries claim a life every 24 seconds, establishing their position among the top ten leading global causes of mortality (World Health Organization, 2018). Beyond the loss of life and the incapacitation of many others, these injuries impose a substantial economic burden, due to the cost of medical treatment of injuries or disabilities. Aiming at the mitigation of injury risks for occupants and pedestrians in a crash scenario, passive vehicle safety systems such as absorption structures (*e.g.*, side sills, longitudinal and cross members) and the restraint system (*e.g.*, airbags, seats, and seatbelts) are optimized with regard to best possible crashworthiness (Schuhmacher, 2020; Gonter et al., 2021). Due to complex time dependent system behavior in crash scenarios as a result of large deformations, material failure and contact interaction the mechanical design of such systems is highly demanding. In the development, multiple objectives and relationships from numerous domains have to be considered and have to be resolved by the engineers. For addressing mechanical system optimization problems numerical finite element (FE) simulations have become essential, as they offer a platform to quickly evaluate concepts, mitigating the time and resource demands associated with physical tests on individual components or complete vehicle prototypes (Klein, 2015; Schuhmacher, 2020). Subsequently, investigations in today's development are conducted mostly in virtual design space and physical tests are used for ensuring the FE model validity. Attributable to increasing vehicle complexity and variant multitude, the number of numerical crash simulations to optimize the passive vehicle safety systems is expected to increase further. Given that automotive companies typically engage in the development of multiple vehicle series and derivatives, a vast amount of simulation and physical test data is generated. Since the generated data does not serve any purpose after the evaluation, a significant cost and technical potential can be leveraged if data is reused (Kohar et al. 2021). AI-based methods for optimizing vehicle safety systems and the corresponding development processes have also been developed and discussed in literature: Rule mining for design parameters (Diez et al., 2018), the ROLCp value (Rabus et al., 2022) for predicting occupant loads, a fully automated method for outlier detection (Kracker et al., 2022) an algorithm for context-based analysis and event chain reconstruction (Mathieu et al., 2023), as well as data repository discovery based on knowledge graphs (Pakiman et al., 2023) are to be mentioned here.

In response to the multifaceted challenges posed by engineering tasks, the present work proposes a concept to support engineers, aiding them in navigating the diverse array of methods to make informed decisions regarding the strategic deployment across various phases of the development process. To provide a meaningful practical reference, the concept is discussed in the industry use case of passive vehicle safety system development. Hereby, the following three research questions (RQ) are answered within the present work.

RQ:1 Which AI-based methods for optimizing processes in the development of passive vehicle safety systems are currently available?
RQ:2 How can a concept look like in which existing and possible future methods in the intersecting field can be categorized and selected systematically?
RQ:3 To what extent can this concept be generalized to other domains?

2 State of the Art

2.1 Crash Simulations in the Development of Passive Vehicle Safety Systems

Crash simulations are used for verification and validation as well as optimization of mechanical system behavior (Klein, 2015; Schuhmacher, 2020). The development of passive vehicle safety systems is a prominent field of where such simulations are applied. This can be structural behavior of longitudinal members in frontal impacts, but also the interaction of an anthropomorphic test device (ATD) with a restraint system. Simulations are performed on different system levels, *i.e.*, components (*e.g.*, rims), subsystems (*e.g.*, restraint systems), and systems (full vehicle). The simulation process chain according to Klein (2015), as depicted in Figure 1, consists of an input given as computer aided design models and load cases. Load cases can either be specified internally within an organization or have been defined by legal regulations or consumer protection guidelines (Gonter et al., 2021). This information is used to setup the FE simulation models which are then computed, in most cases on large simulation clusters. In the next step, the engineer postprocesses the generated output by verifying the results, validating the concept according to requirements defined in the product specification sheets and documenting the results. In the end, simulation repositories are used for archiving substantial amounts of simulation data (Iza Teran and Garcke, 2015).

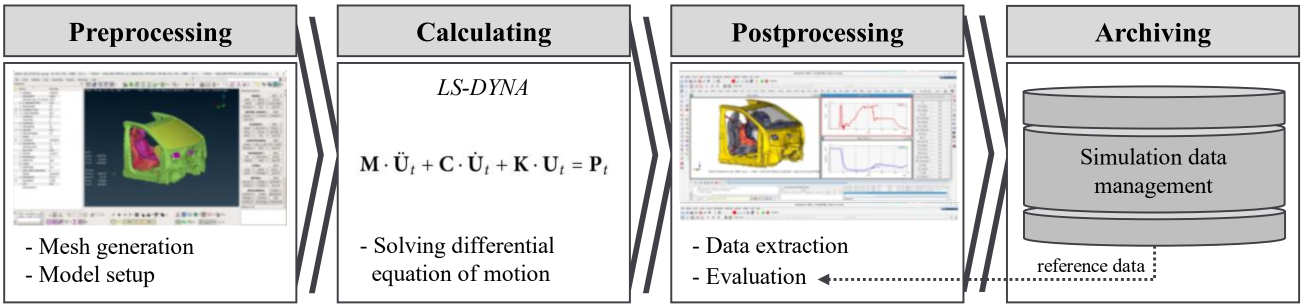

Figure 1. Crash simulation process according to Klein (2015) based on Mathieu et al. (2023)

2.2 Artificial Intelligence in the Development of Passive Vehicle Safety Systems

Given the importance and considerable development effort involved in passive vehicle safety systems, along with the growing trend of effectively integrating emerging technologies such as AI into development processes, a variety of research works have already explored this area. To ensure a solid foundation of the present work, a systematic literature review according to Figure 2 leaning on the PRISMA-P procedure (Moher et al., 2015) has been performed.

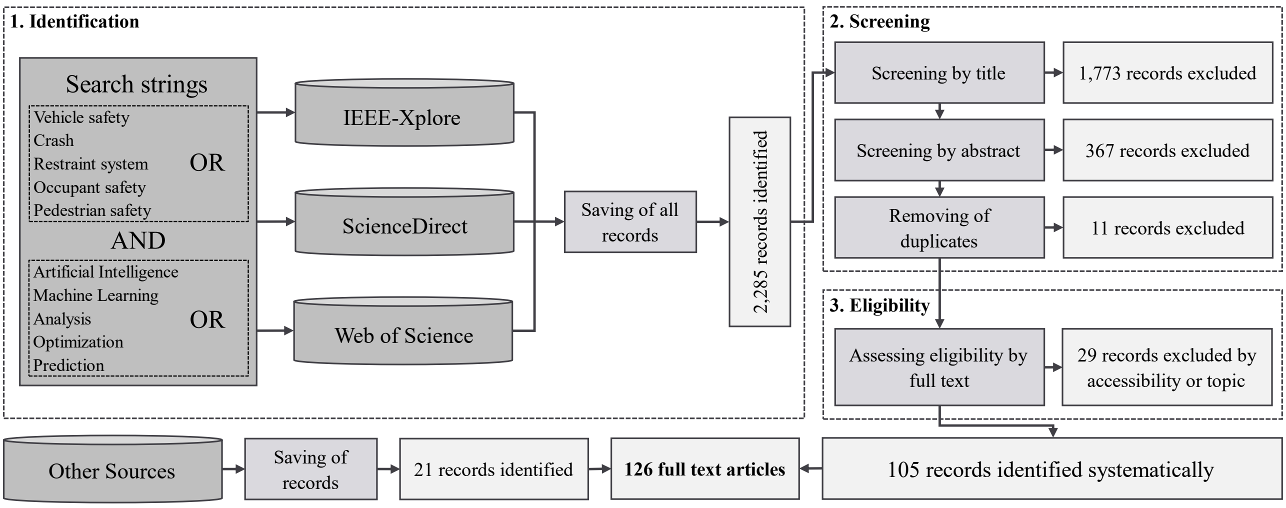

Figure 2. Scheme of the performed systematic literature review leaning on the PRISMA-P procedure of Moher et al. (2015)

The search strings displayed in Figure 2 have been used to search three different databases. The resulting 2.285 records have been filtered separately by screening abstract and title. Eleven duplicates are removed before full text eligibility is analyzed. 105 articles are systematically found and considered to be relevant for the topic. An additional 21 articles were incorporated through further searches based on the systematically identified articles in other databases, particularly Google Scholar. In total, 126 articles are used as a theoretical basis for the present work.

Developmental efforts in passive vehicle safety are divided between physical testing and simulation activities, with physical testing, in the present era, primarily applied for the validation and verification of virtual FE models due to digitization and the increased degrees of freedom in the virtual design space (Klein, 2015; Schuhmacher, 2020). Therefore, 78% of the systematically identified literature focuses on optimization along the simulation process as shown in Figure 1. The most frequently cited reasons for the advantageous implementation of these concepts include the enhanced technical merit of solutions, quality assurance, an increased understanding of the systems, as well as the consequential reduction in development time and costs. Attributable to the predominant focus of the literature on virtual development processes, the authors propose a sorting of the most relevant concepts along the simulation process as depicted in Figure 1.

2.2.1 Process Optimization: **Preprocessing**

Optimizing the preprocessing refers to the faster setup and definition of a FE model. For the simulation, the geometry needs to be discretized with a mesh (Klein, 2015). To improve the meshing process, Zhang et al. (2020) presented a machine learning (ML) method to predict two-dimensional mesh topologies for unseen geometries. By using such methods, the high time consumption for meshing large structural parts such as a full body-in-white can be reduced. For quality assurance, Sprave and Drescher (2021) proposed a ML-based method to automatically examine and ensure mesh quality for best possible foundation for the simulation. A feed forward neural network and tree-based model were trained to solve an element wise classification problem. The class labels for the dataset were obtained by expert evaluations. However, even though the approach showed general practical applicability, the obtained results for both models, at a reasonable precision threshold misclassified up to 23% of the elements. Another aspect of the preprocess is the definition of material properties for the simulation models. Attributable to intense physical testing the material property identification and calibration of the properties in the virtual model can take a significant amount of time. Automated pipelines for definition of complex material properties such as the behavior of two-phase materials based on microstructural images as discussed by Ford et al. (2020) or the ML-based calibration of failure models of composite parts by Eskandariyun et al. (2023) show significant potential in this aspect. Garcke et al. (2017) proposed a ML-based method for relating two FE models regarding geometry, thickness, material properties, rigid body elements and spotwelds, allowing a quick comparison independent of mesh-size. The proposed method was validated on an open-source FE simulation model.

2.2.2 Process Optimization: **Calculating**

To improve the calculation process, ML-based prediction models can be used as a surrogate for the FE simulation and predict the trained result variables directly. Another option is the integration within the FE solver itself. For the **surrogate** approach the **input of the models** can be categorized into parametrized approaches (Thiele et al., 2006; Horii, 2017; Rabus et al., 2022) and non-parametrized approaches (Kohar et al., 2021). Parametrized approaches aim to describe the system using numeric values, such as those related to the restraint system configuration or the thickness of a metal sheet. Rabus et al. (2022) used features from the vehicle crash deceleration curve as well as features describing the vehicle and restraint system configuration for predicting a surrogate value named ROLCp. The ROLCp displays high correlation to the chest acceleration of an ATD on the driver position and can be used for minimizing occupant loads in the early design phase before full occupant simulation models are available. In non-parametrized approaches the model is unaware of specific parameters and thus needs to learn the dependencies purely from data. Kohar et al. (2021) predicted the full structural behavior of a crash box under a dynamic axial load. The geometry is transformed into a voxel space whereby the time dependent behavior is trained to a long short-term memory artificial neural network. With respect to the **output of the models**, a distinction has to be made between scalar and (time) series data. While Rabus et al. (2022) predicted a time-independent scalar surrogate value, Horii (2017) predicted multiple scalar occupant loads for Japan NCAP, including Head Injury Criterion, chest acceleration, and femur loads. One dimensional time series data was predicted in the work of Belaid et al. (2021) in form of a chest acceleration curve from an ATD. Kohar et al. (2021) as well as Greve et al. (2022) were able to predict the movement for a set of nodes over time, which corresponds to two and three-dimensional time series data respectively. Regarding the **application scenario** of the model local and global approaches can be distinguished. Local approaches as discussed by Horii (2017), Thiele et al. (2006) or Joodaki et al. (2021) are prediction models trained for one specific problem statement. In these cases, it is the restraint system optimization and design exploration for one distinct vehicle model respectively. In contrast, Belaid et al. (2021) as well as Rabus et al. (2022) use a database consisting of various vehicle types and configurations. Hence, these models are able to generalize between different vehicle types and can be used in the early phases of the development for future product generations to define promising directions in system design. In combination with an optimization algorithm which automatically specifies the FE model configuration as part of the preprocess automatic design exploration can be achieved (Horii, 2017). A more user interactive approach for the engineers manually exploring design spaces is discussed by Thiele et al. (2006). Pfaff et al. (2021) presented a method for learning time dependent behavior in mesh-based simulations with graph neural networks. The presented model uses an encode-process-decode architecture, which is trained with one-step supervision. The model can be applied iteratively to generate long trajectories at inference time.

Methods for supporting processes **within the FE solver** can also be optimized aiming at a reduction in runtime and increased accuracy. This aspect is particularly relevant for high non-linear problem statements (Pantidis and Mobasher, 2023). Capuano and Rimoli (2019) presented a ML approach for generating a direct relationship between the element state and the forces, which avoids specifying the internal displacement field. This procedure eliminates the need for numerical iterations and thus reduces the time required for solving the model. Pantidis and Mobasher (2023) integrated a neural network into the element formulation to model non-local continuum damage mechanics. The approach successfully tackled the drawbacks of mesh size dependance and computational cost.

2.2.3 Process Optimization: **Postprocessing**

The optimization of the postprocess incorporates extracting information about anomalous behavior, possible root causes or rules automatically in a set of FE simulations. The analysis of the simulation output can be performed based on geometry data (*e.g.*, the nodal displacement or element stress field) but also on sensor signal data (*e.g.*, section force or pressure) or distinct surrogate values calculated based on the simulation output (*e.g.*, maximum displacement). Research to date has mainly focused on processing **geometry data** describing the time dependent behavior of nodes and elements since this the most general data source (Diez et al., 2018; Kracker et al., 2023). One significant problem that arises in the processing of mesh-based data is the uniform representation as a result of geometric discretization (Iza Teran and Garcke, 2019). Identical geometries may be discretized with different arrangements and numbers of nodes and elements. Subsequently, an additional step is required for transforming the data into a uniform space. A variety of methods have been presented in literature (Kracker et al., 2020). Diez et al. (2018) calculated the geometric center of gravity along the longitudinal axis before the surrounding elements are projected onto the specified axis. This method allows the processing of profile shaped components like a longitudinal member but is conditionally feasible for the processing of planar components (Kracker et al., 2020). Alternative methods use the projection of mesh-data into a three-dimensional voxel grid (Kracker et al., 2020), a modified virtual spherical detector surface approach (Sprügel et al., 2017), the mapping of different FE meshes to one reference simulation (Iza Teran and Garcke, 2015), or a coherent point cloud algorithm (Greve et al., 2022). As a result of the transformation additional computational cost, memory, and storage, as well as a certain loss of information have to be considered. Recent research on postprocess optimization emphasizes on unsupervised ML techniques, in particular dimensional reduction, whereby a variety of approaches, *i.e.*, Principal Component Analysis (PCA) (Thole et al., 2010; Kracker et al., 2023), non-linear t-distributed stochastic neighbor embedding (Kracker et al., 2020) or the Laplace-Beltrami operator (Iza Teran and Garcke, 2019) were discussed. For analyzing a set of simulations Kracker et al. (2023) presented an outlier detection algorithm, which can automatically highlight anomalous behavior of components. Thole et al. (2010) showed that deformation modes calculated based on a PCA can be correlated and used for specifying possible root causes for certain behavior in the system. The concept was demonstrated on the spitwall in a full vehicle crash. To support engineers in decision making during the design phase, Ackermann et al. (2008) proposed a method for determining important geometry parameters in the simulation input by also using a PCA approach. Diez et al. (2018) investigated rule mining to determine geometry parameters related to the deformation modes of a front bumper in a frontal impact crash scenario, using an approach that includes supervised and unsupervised learning methods. Based on the rules engineers are enabled to specify parameters to realize certain deformation behavior. The **sensor signal data** describes system behavior more superficially comprising indirect information about geometric effects (Mathieu et al., 2023). With respect to occupant safety, time series data is particularly important as these are the basis for the calculation of surrogate values like the Head Injury Criterion, chest intrusion or acceleration, relevant for legal regulations and consumer protection guidelines (Gonter et al. 2021). Mathieu et al. (2023) proposed a method for visualizing deviations in multivariate sensor data in sparse occupant crash simulation datasets. Based on the calculated deviation scores the automated reconstruction of a possible event chain was performed, highlighting influential and large deviations from an amplitude and time perspective. The approaches are particularly important for ensuring quality of the simulations as well as increasing system understanding. Approaches within postprocessing are crucial for ensuring simulation quality, extracting knowledge, and thereby enhancing the engineers' understanding of the system.

2.2.4 Process Optimization: **Archiving**

For storing the data and making it available in later phases of the development large simulation data repositories are used. Since the relevant information was extracted in the postprocess, the data serves in most cases no further purpose (Kohar et al., 2021). Depending on the scenario, methods used for postprocessing a set of simulations could possibly be used to analyze a whole database. However, in this case the terminology archiving refers to more overarching approaches as proposed by Pakiman et al. (2023) to extract knowledge from a simulation database containing multiple development phases of a vehicle. They used the internal energy curve of crash simulations for extracting features, for instance, the initial absorption time, the maximum energy absorption, and the time where the maximum energy absorption occurs. These features were used to set up a knowledge discovery assistant based on a graphical database to cluster simulations according to their similarities over different vehicle development phases. In a subsequent step, such machine-readable knowledge can be extracted, processed with supervised ML methods, and can offer added value in the development processes. The great amount of large FE simulations requires a lot of storage and is inert when used as a reference for giving context to newly performed simulations as part of a comparison within the postprocess. Iza Teran and Garcke (2015) presented a dimensional reduction approach for compressing data in a repository. A concept for the use and interaction as well as further processing options with a user during development also were discussed.

2.3 Situation Appropriate and Use Case Dependent Method Selection in Product Development

According to Albers et al. (2015; 2019) the majority of today's products are developed in generations. Hence, most products already exist on the market and future generations are either revised versions or optimized regarding specific attributes. The development processes are defined by iterative optimization cycles, alternating between analyzing reference products or concepts to establish development objectives and synthesizing the new generation to a desired state. This iterative refinement is done by applying different methods and continues until an optimal solution is obtained. This is referred to as the problem-solving cycle, which is depicted in Figure 3 and considered to be a fundamental principle in product development. Since the formulation according to VDI 2221 (2019) is rather general, approaches for a more explicit formulations for specific domains and fields can be developed (König et al., 2023).

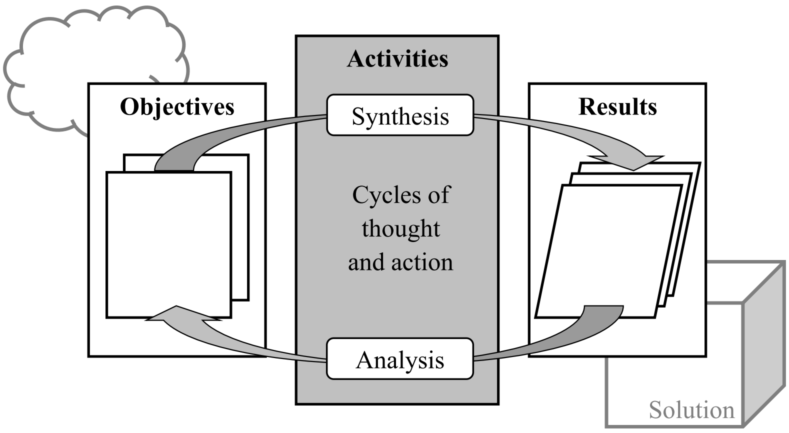

Figure 3. Problem solving cycle in product development, adapted from VDI 2221 (2019)

Wach (1993) and Helbig (1994) identified general characteristics of product development methods, which can be applied to describe and categorize different methods. Based on the characteristics Zanker (1999) proposed an individual modification and arrangement of methods depending on the situation in the development process. In the subsequent work by Braun and Lindemann (2004), a more systematic and transparent method description was developed and the high dependency of the method characteristics on the use case was emphasized. According to Pahl and Beitz (2007) a differentiation can be drawn between usable solution finding and assessment methods, methods for product planning and task clarification, methods for conceptualizing, designing, elaborating and quality-assuring product development. Hence, methods are grouped according to the objectives they support. The method selection process was automated in the conceptual tool presented by Albers et al. (2015), which suggests methods depending on the situative problem statement occurring in engineering design. This corresponds to the situation- and demand-oriented combination of structuring and flexible elements as part of the agile systems design proposed by Albers et al. (2019). Based on the methods, which form the foundation, the challenge lies in the efficient formulation of development processes considering all relevant scenarios. This can for instance be realized with the supplementation of methods based on a systematic recommended course of action (Jänsch, 2007). The implementation of diverse methods in development processes is facilitated through the use of instructional elements for instance consisting of control questions, checklists, or process explanations. These are designed to underscore the advantages regarding the product itself but also the processes and support engineers in their working routines. Noteworthy aspects regarding the efficient selection of methods refers to the disparities in process characteristics across different organizations and industries (VDI 2221, 2019; Wilmsen, 2022) as well as the varying experience and expertise of the involved engineers (Jones, 1970). Subsequently, the previously discussed relatively generic approaches form the basis for a concretization depending on the application field, since processes and associated methods should always be adapted in accordance with the specifics needs and demands. Examples include the work of König et al. (2023) in the intersecting field of lightweight design and design for sustainability or the work of Wilmsen (2022) in the process development for the automotive predevelopment. However, a clear and systematically recommended course of action is lacking for the situational and use case-dependent selection and categorization of AI-based methods, especially in such specialized fields with high practical relevance in the development of future vehicle generations.

3 Framework for Selection and Categorization of Artificial Intelligence-based Methods

The problem-solving cycle serves as a basis for the present work and is applied to the intersecting field of AI and virtual development processes in passive vehicle safety system development. A possible target group can be an organization or organizational unit responsible for the development of vehicle safety systems. Figure 4 depicts the proposed framework. The objectives and results shown there are specified from a local perspective within the intersecting field in accordance with the general formulations found in VDI 2221 (2019). **Objectives** are an improved vehicle safety, savings in development time and costs, an increase of the degree of innovation as well as the gain of knowledge for the involved engineers. **Results** refer to the contributions of the organizational unit to the vehicle development process in general and are therefore specified as the system models, solution concepts and requirements, system architecture, documentation. Results from other fields need to be analyzed and considered from a vehicle safety perspective, whereby potentially conflicting targets need to be resolved during development in order to develop the best possible product.

As visualized in Figure 4, a matrix scheme is used to systematically organize existing methods in the intersecting field. The methods in the intersecting field are considered as **activities** the engineer performs when applying these during development. The specification of the axis builds upon the comprehensive literature review presented in Section 2. The identified emphasis in the application of AI-based methods for the development of passive vehicle safety systems is centered on the application of ML techniques to optimize the extensive simulation processes. In general, ML is considered a subset of AI focusing on the development of algorithms that enable computers to learn from data and make predictions or decisions (ISO 23053, 2022). The vertical axis of the matrix incorporates the crash simulation process consisting of the preprocessing, calculation, postprocessing and archiving of the data (Iza Teran and Garcke, 2015; Klein 2015). The horizontal axis contains the main approaches according to the framework for AI systems using ML proposed in ISO 23053 (2023), *i.e.*, supervised learning, unsupervised learning, and reinforcement learning. Algorithm types, for instance decision trees or neural networks as examples for supervised learning techniques, are thus included in the bundle representation. If multiple ML approaches or parts of the simulation process are covered, corresponding fields are highlighted together. Each of the method bundles may contain multiple methods corresponding to the respective axis labels, since methods may have similar purposes and are based on similar techniques. For instance, the work of Iza Teran and Garcke (2019) and the work of Kracker et al. (2023) both optimize the postprocess but are based on two different dimensionality reduction techniques, both belonging to the unsupervised learning branch. If required, additional fields can be added, or a more detailed representation, *e.g.*, of the algorithm types, can be depicted depending on user preference. The knowledge of how a certain method is working and how it is applied as well as which and how much data is used at what time, connects the simulation process and the ML methods. This kind of knowledge is seen as the foundation for integrating new concepts and engineering methods into existing processes and has to be made available to all relevant engineers involved. This aspect is crucial for organizations as it gives them a lasting competitive advantage over their rivals in today's engineering landscape (Gao and Bernard, 2018). Since data is a central resource in this context and the engineer needs to provide suitable interfaces for processing or visualization. The literature review showed that different data types can be processed. In order for engineers to maintain the overview, especially with regard to the comparison or selection of methods in an industry context, a clear representation, as indicated in Figure 4, is substantial. Implementation can be realized by static posters, or an interactive dashboard based on Figure 4. Standardized method description templates that provide a uniform description format are essential for knowledge storage for both implementation scenarios. While a detailed set up of method templates particularly for AI methods in product development will be covered in future work, the template provided by Ponn (2007) is considered a solid foundation. In documentation, particular emphasis should be placed on data and interfaces, as these are primarily relevant for application by the engineers.

The main dependencies of where and how the **application** of methods takes place, *i.e.*, activities are performed, is defined based on the previously discussed literature review, and illustrated in Figure 4 with a cuboid representation. Direct dependencies arise due to the factor that ML algorithms are data driven (ISO 23053, 2023). Apart from the algorithm a method is based on, the quantity, type, and dimensionality of the data play a major role and thus influence the application. Detailed information or mathematical constraints if available, *e.g.*, a minimum size of the data set, is recommended to be included in the method description template. From an engineering perspective, three relevant dependencies with regard to data were identified: development time, system level and engineering task. In very early concept phases not many simulations exist since the development just has been initialized. As development time progresses, more and more datasets become available as simulations or tests are carried out. The system level according to VDI 2206 (2021) denotes to the terminology described in and refers to component level (*e.g.*, airbag or seatbelt), substem level (*e.g.*, restraint system or vehicle front section) and system level (*i.e.*, full vehicle). Large simulation models representing the full vehicle system are computationally expensive (Schuhmacher, 2020), and the amount of generated data is thus typically lower, while the degrees of freedom and the design space is larger. Engineering tasks can be the optimization of system behavior, the validation of concept, design, or material changes as well as robustness assessments (Klein, 2015; Schuhmacher, 2020). Typically, larger amount of data is generated for robustness or optimization campaigns, whereby the coverage, size and distribution of the analyzed design spaces may vary. Furthermore, tasks can be assigned to disciplines, which in turn, depending on the organizational structure, can be assigned to projects. Disciplines in the considered field are structural, pedestrian, and occupant safety (Gonter et al., 2021). From the perspective of an automotive company, which normally has a portfolio of multiple vehicle series and derivates, tasks and or disciplines reoccur multiple times in different vehicle projects at different times. The application scheme also enables the depiction of interrelations and added values of methods in an application-oriented manner. An example here is a method to incorporate physical measured uncertainty, for instance in the airbag unfolding (component level), into a simulation on subsystem or system level. Or the knowledge transfer from one to another project, for instance with optimization strategies as they can be learned by reinforcement learning agents which could be applied in various projects (Sutton and Barto, 2020). Another example is the provision of knowledge at earlier stages, as demonstrated in the method of Rabus et al. (2022), which is particularly helpful due to the high degree of freedom in the initial phases of the development (Bender and Gericke, 2021).

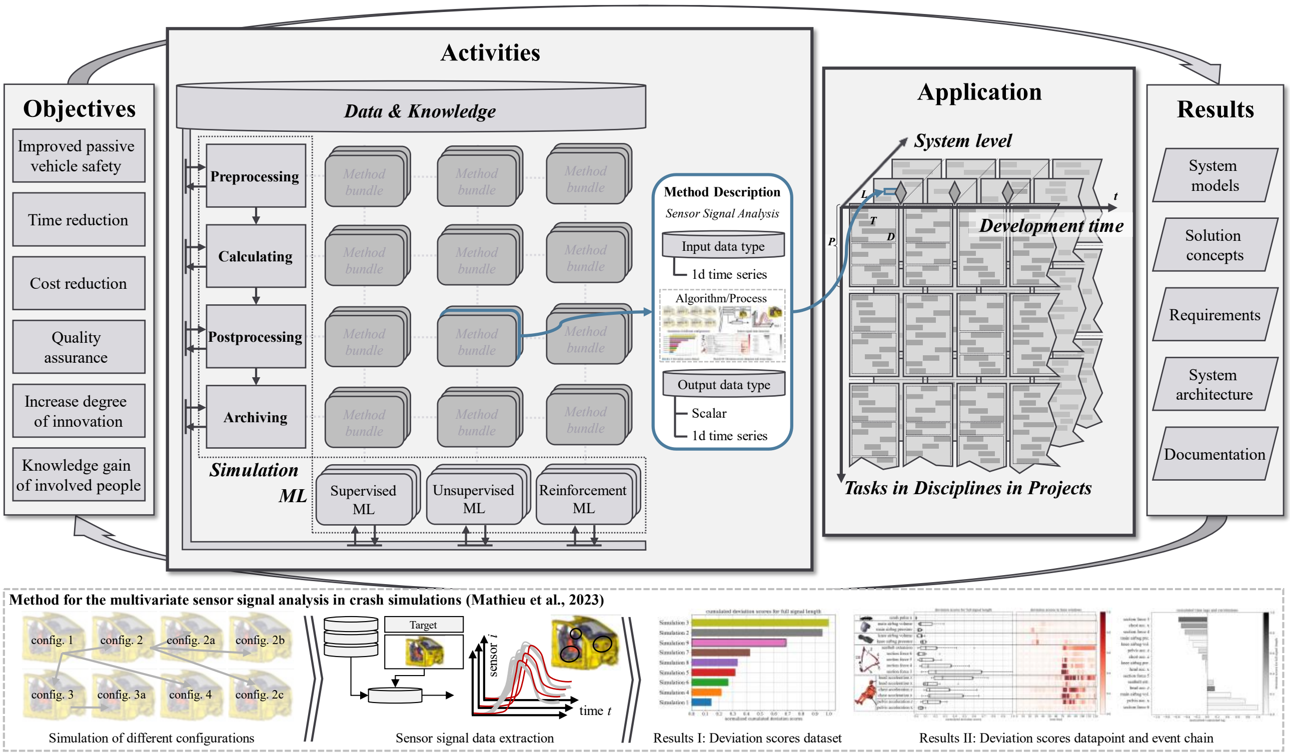

Figure 4. Framework for the selection of AI-based methods to support the development of passive vehicle safety systems

3.2 Systematic Categorization of Methods

For the application in industry scenarios, the framework can be used for systematically categorizing existing methods. It also allows for easy extension for future concepts if these are not covered by the present scheme. This enables the identification of whether similar or identical concepts already exist, potentially serving the same purpose. Therefore, when a decision has to be made regarding the acquisition of a new tool or the internal development of a new method, redundant procurement or work may be saved. Furthermore, possible blind spots can be identified where new methods could provide added value. According to the framework visualized in Figure 4, categorization is performed by the following steps:

- Select the parts of the simulation process which are supported by using the method.
- Select the ML approach that is used.
- Specify method or algorithm specific information and or constraints such as input and output data types.
- Specify development process specific information and or constraints, *i.e.*, where the method is applicable, according to task, discipline, project, development time, and system level.
- If possible, highlight where and how knowledge is transferred by applying the method.

In order to explain the procedure in more detail, an exemplary method selection of the event chain reconstruction based on multivariate sensor data in the work of Mathieu et al. (2023) is included. The method briefly shown in the lower part of Figure 4, aims to optimize the postprocess by providing an automatically generated report visualizing the system behavior for one specific simulation in the context of other simulations in the dataset. The engineer is provided with targeted information when newly performed simulations are compared with previous ones. The used k-means clustering algorithm for calculating deviation scores is an unsupervised ML approach. The input data type of the method is one-dimensional time series data since it is purely based on sensor signal data as output by the crash simulations. The output data are deviation scores given in series as well as parameter data, which is visualized using heatmaps as well as box- and barplots. The method validation has been performed within the industry use case of restraint system design in frontal crash scenarios and demonstrates a reduced evaluation time, increase in system understanding and simplified quality assurance. The industry simulation models used are reduced sled models that represent subsystems. Since a validation has not yet been done for component or system level simulations, the method is subsequently considered to be only applicable for subsystem level. The method can be used across projects and disciplines, whereby the use is feasible for tasks that involve crash simulations. Knowledge transfer to another task or system level or development phase cannot be realized. It has been shown that a small number of simulations can be processed, making the concept also viable for early phases where small number of simulations are available. The highlighted aspects need to be incorporated into the description template indicated in Figure 4.

3.3 Systematic Selection of Methods

The previously discussed categorization serves as a foundation for the now discussed systematic method selection. Based on the assigned categories certain methods can be included or excluded depending on their affiliation, which serves as a guidance for the engineers. This can also help to familiarize engineers with new methods in general, which can increase the conservation of knowledge in the organization and thus the efficiency of development (Gao and Bernard, 2018). Figure 5 depicts the engineering question, which arises in structural development of vehicles in the early design phases since detailed FE models for occupant safety are not yet available (Rabus et al., 2022). The considered task is structure assessment in terms of occupant loads and the discipline is the validation of structure design. Due to the early phase application a highly generalized model for cross-project use is required since no detailed vehicle information is available yet. The system level is considered to be subsystem, as occupant loads in frontal impacts are normally determined using sled models (Thiele et al., 2006). Two suitable methods proposed in literature are found, whereby both have the same input data types with a crash pulse as well as vehicle parameters. The output data types and data processing however significantly differs, even though both methods use supervised learning approaches. Belaid et al. (2021) use a convolutional neural network architecture to predict a chest acceleration curve (time series data) of the occupant on the driver seat. Rabus et al. (2022) predict a surrogate value (scalar data) correlating to the maximum chest acceleration of the occupant on the driver seat with a tree-based algorithm. Rabus et al. (2022) also incorporate explainable AI techniques to make the results more understandable for engineers. If necessary, further differentiation can be achieved on the basis of ML methods or simulation processes as well as method specific attributes such as the output data type. In this case, the engineer is left to decide how to proceed.

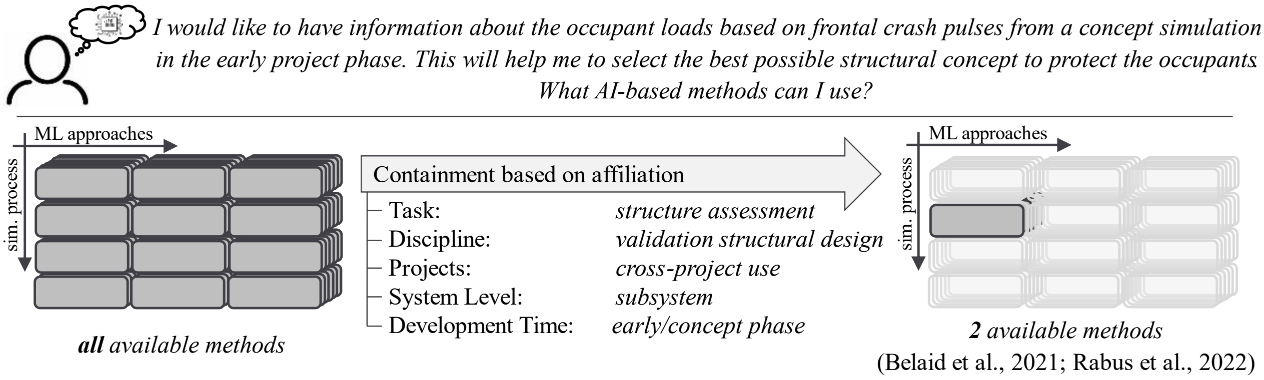

Figure 5. Selection of methods according to attributes

3.4 Transfer of the Framework to Other Intersecting Fields

The proposed framework has been discussed on a very specific but highly relevant intersecting field of application within vehicle development. By categorizing methods, systematic selection and guidance through the new, dynamic, and complex field has been demonstrated. Aspects such as the exact naming of tasks or the subdivision of ML approaches are defined modular and thus allow for easy customization. To create more value from the proposed framework, a transfer scenario to another intersecting fields is briefly discussed. For instance, lightweight design and sustainability as discussed in the work of König et al. (2023). Examples for the overarching objectives and outcomes can be an overall weight reduction or reduced resource consumption as well as a functional system architecture or three-dimensional system model. Relevant methods can also be systematically arranged in the activity segment of Figure 4. The product life cycle as a key element of sustainability analysis can be plotted on the vertical axis. On the horizontal axis, various lightweight design methods can be plotted, clustered according to approaches in the lightweight design field such as conceptual, shape or manufacturing lightweight design. The phases of how methods are applied depends on the development time (Albers et al., 2015), but could also be extended by further dependencies which can help engineers during application. An example can be the requirement, logical or functional description of the system. A lightweight design analysis method considering the whole product lifecycle to holistically reduce resource consumption has been proposed in the work of König et al. (2024). The method is applicable in the early design phase within the functional design space.

4 Conclusion and Outlook

The conclusions are formulated in response to the three research questions from Section 1 as follows. To address RQ:1, a systematic literature review was conducted, which identified relevant AI-based methods in the field of passive vehicle safety. Due to the strong focus on virtual development processes and ML, relevant contributions were categorized and discussed along the simulation process. In response to RQ:2, for the systematic categorization and selection of methods, a framework in accordance with existing method selection concepts in product development is proposed. Management decisions, for example the development or purchase of new tools, are systematized by providing categories where tools support the processes. This prevents redundant purchases or development efforts and highlights research gaps. The engineers are supported in selecting methods during activities in development which can leverage significant time and cost potentials in addition to the efficiency gains by the use of the methods themselves attributable to the best possible use scenario of each method. The framework was verified by the systematic categorization of a ML-based multivariate sensor signal analysis and the selection of possible methods in a typical engineering task in the structural assessment of vehicles regarding occupant loads in the early phase. The ability for guidance and decision making through the systematic approach has subsequently been demonstrated. In order to answer RQ:3, the generalization for other intersecting fields, such lightweight design and sustainability was briefly discussed. A possible definition of the activities and areas of application as well as the integration of a possible method was proposed. This is intended to provide an outlook for future work as well as an impulse to continue capitalizing on the idea.

Hence, the in-depth analysis regarding the generalization capabilities of the framework in the field product engineering in general is considered in follow-up work. Within the present work, the proposed framework only has been verified based on the discussion of practical examples. A validation of the approach will hence also be addressed in future work. This aspect presents a challenge as a procedure must be devised to validate the concept effectively within reasonable time period, as development cycles of new vehicles typically span multiple years.

References

Ackermann, S., Gaul, L., Hambrecht, T., Hanss, M., 2008. Principal Component Analysis for Detection of Globally Important Input Parameters in Nonlinear Finite Element Analysis, Weimar Optimization and Stochastic Days. Weimar.

Albers, A., Reiß, N., Bursac, N., Walter, B., Gladysz, B., 2015. InnoFox – Situationsspezifische Methodenempfehlung im Produktentstehungsprozess, Stuttgarter Symposium für Produktentwicklung. Stuttgart.

Albers, A., Heimicke, J., Spadinger, M., Reiss, N., Breitschuh, J., Richter, T., Bursac, N., Marthaler, F., 2019. A systematic approach to situation-adequate mechatronic system development by ASD - Agile Systems Design. Procedia CIRP, 84, 1015-1022.

Bender, B., Gericke, K. (Eds.), 2021. Pahl/Beitz Konstruktionslehre. Springer Berlin Heidelberg, Heidelberg.

Berisha, B., Lobov, A., 2021. Overview and Trends for Application of AI Methods for Product Design. IEEE 19th International Conference on Industrial Informatics, Palma de Mallorca, pp. 1-8.

Belaid, M.K., Rabus, M., Krestel, R., 2021. CrashNet: an encoder–decoder architecture to predict crash test outcomes. Data Mining and Knowledge Discovery 35, 1688–1709.

Braun, T., Lindemann, U., 2004. Method adaption - A way to improve methodical product development. DS 32: Proceedings of DESIGN 2004, the 8th International Design Conference, Dubrovnik, pp. 977-982.

Capuano, G., Rimoli, J.J., 2019. Smart finite elements: A novel machine learning application. Computer Methods in Applied Mechanics and Engineering 345, 363-381.

Diez, C., Kunze, P., Toewe, D., Wieser, C., Harzheim, L., Schumacher, A., 2018. Big-Data Based Rule-Finding for Analysis of Crash Simulations, in: Schumacher, A., Vietor, T., Fiebig, S., Bletzinger, K.U., Maute, K. (Eds.), Advances in Structural and Multidisciplinary Optimization. Proceedings of the 12th World Congress of Structural and Multidisciplinary Optimization, Springer Nature, Cham, pp. 396–410.

Eskandariyun, A., Joseph, A., Stere, A., Byar, A., Fomin, S., Kabir, M., Dong, J., Zobeiry, N., 2023. A Combined Finite Element and Machine Learning Approach to Accelerate Calibration and Validation of Numerical Models for Prediction of Failure in Aerospace Composite Parts. Proceedings of the ASME 2023 Aerospace Structures, Structural Dynamics, and Materials Conference, San Diego.

Ford, E., Maneparambil, K., Rajan, S., Neithalath, N., 2021. Machine learning-based accelerated property prediction of two-phase materials using microstructural descriptors and finite element analysis. Computational Materials Science 191, 110328.

Gao, J., Bernard, A., 2018. An overview of knowledge sharing in new product development. The International Journal of Advanced Manufacturing Technology 94, 1545–1550.

Garcke, J., Pathare, M., Prabakaran, N., 2017. ModelCompare, in: Griebel, M., Schüller, A., Schweitzer, M. (Eds.), Scientific Computing and Algorithms in Industrial Simulations, Springer Nature, Cham, pp. 199–205.

Gonter, M., Knoll, P., Leschke, A., Seiffert U., Weinert, F., 2021. Fahrzeugsicherheit, in: Pischinger, S., Seiffert, U. (Eds.), Vieweg Handbuch Kraftfahrzeugtechnik. ATZ/MTZ-Fachbuch, Springer Vieweg, Wiesbaden, pp. 1073-1160.

Greve, L., van de Weg, B.P., 2022. Surrogate modeling of parametrized finite element simulations with varying mesh topology using recurrent neural networks. Array 14, 100137.

Helbig, D., 1994. Entwicklung produkt- und unternehmensorientierter Konstruktionsleitsysteme (Doctoral dissertation). Technical University of Berlin, Berlin.

Horii, H., 2017. Multi-objective Optimization of Vehicle Occupant Restraint System by Using Evolutionary Algorithm with Response Surface Model. International Journal of Computational Methods and Experimental Measurements 5, 163-173.

ISO 23053, 2023. Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML). Beuth, Berlin.

Iza Teran, R., Garcke, J., 2015. Machine Learning Approaches for Repositories of Numerical Simulation Results, 10th European LS-DYNA Conference. Würzburg.

Iza Teran, R., Garcke, J., 2019. A Geometrical Method for Low-Dimensional Representations of Simulations. SIAM/ASA Journal on Uncertainty Quantification 7, 472–496.

Jänsch, J., 2007. Akzeptanz und Anwendung von Konstruktionsmethoden im industriellen Einsatz: Analyse und Empfehlungen aus kognitionswissenschaftlicher Sicht (Doctoral dissertation). Technical University of Darmstadt, Darmstadt.

Jones, J.C., 1970. Design methods: seeds of human futures. Wiley-Interscience, London.

Joodaki, H., Gepner, B. and Kerrigan, J., 2021. Leveraging machine learning for predicting human body model response in restraint design simulations. Computer Methods in Biomechanics and Biomedical Engineering 24, 597-611.

Klein, B., 2015. FEM: Grundlagen und Anwendungen der Finite-Element-Methode im Maschinen- und Fahrzeugbau. Springer Fachmedien Wiesbaden, Wiesbaden.

Kohar, C.P., Greve, L., Eller, T.K., Connolly, D.S., Inal, K., 2021. A machine learning framework for accelerating the design process using CAE simulations: An application to finite element analysis in structural crashworthiness. Computer Methods in Applied Mechanics and Engineering 385, 114008.

König, K., Kaspar, J., Vielhaber, M., 2023. Sustainable Systemic Lightweight Design (S2LWD) - Guidance for the heuristic application of lightweight design within an integrated product development process. Procedia CIRP, 119, 333-338.

König, K., Mathieu, J., Vielhaber, M., 2024. Resource conservation by means of lightweight design and design for circularity - A concept for decision making in the early phase of product development. Resources, Conservation and Recycling, 201, 107331.

Kracker, D., Garcke, J., Schumacher A., 2020. Automatic Analysis of Crash Simulations with Dimensionality Reduction Algorithms such as PCA and t-SNE, 16th International LS-DYNA Users Conference. Virtual Event.

Kracker, D., Dhanasekaran, R.K., Schumacher, A., Garcke, J., 2023. Method for automated detection of outliers in crash simulations. International Journal of Crashworthiness 28, 96–107.

Mathieu, J., Di Roberto, M., Vielhaber, M., 2023. A data-driven methodology for the automated analysis and explanation of system behavior in crash simulations, 14th European LS-DYNA Conference. Baden-Baden.

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., Stewart, L.A., 2015. Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. Systematic Reviews 4, 1.

Pakiman, A., Garcke, J., Schumacher, A., 2023. Knowledge discovery assistants for crash simulations with graph algorithms and energy absorption features. Applied Intelligence 53, 1-20.

Pantidis, P., Mobasher, M.E., 2023. Integrated Finite Element Neural Network (I-FENN) for non-local continuum damage mechanics. Computer Methods in Applied Mechanics and Engineering 404, 115766.

Pfaff T., Fortunato M., Sanchez-Gonzalez A., Battaglia, P.W., 2021. Learning mesh-based simulation with graph networks, 9th International Conference on Learning Representations. Online Event.

Rabus, M., Belaid, M.K., Maurer, S.A., Hiermaier, S., 2022. Development of a model for the prediction of occupant loads in vehicle crashes: introduction of the Real Occupant Load Criterion for Prediction (ROLCp). Automotive and Engine Technology 7, 229–244.

Rudolf, T., Schürmann, T., Skull, M., Schwab, S., Hohmann, S., 2022. Data-Driven Automotive Development: Federated Reinforcement Learning for Calibration and Control. 22. Internationales Stuttgarter Symposium, Springer Fachmedien, Wiesbaden, pp. 369–384.

Schuhmacher, A., 2020. Optimierung mechanischer Strukturen. Springer Vieweg Berlin Heidelberg, Berlin.

Schweitzer, G., Bitzer, M., Vielhaber, M., 2023. Engineering Graph as an Approach to Support Design Decisions in Product Development, in: Proceedings of the Design Society: 24th International Conference on Engineering Design (ICED23), pp. 1625–1634.

Sprave, J., Drescher, C., 2021. Evaluating the Quality of Finite Element Meshes with Machine Learning. ArXiv, 2107.10507.

Sprügel, T., Schröppel, T., Wartzack, S., 2017. Generic approach to plausibility checks for structural mechanics with deep learning, in: Proceedings of the 21st International Conference on Engineering Design (ICED 17) Vol 1: Resource Sensitive Design, Design Research Applications and Case Studies, Vancouver, pp. 299–308.

Sutton, S., Barto A., 2018. Reinforcement Learning: An Introduction. A Bradford Book, Cambridge.

Thiele, M., Müllerschön, H., van den Hove, M. and Mlekusch, B., 2006. Optimization of an Adaptive Restraint System Using LS-OPT and Visual Exploration of the Design Space Using D-SPEX, 9th International LS-DYNA Users Conference. Detroit.

Thole, C.A., Nikitina, L., Nikitin, I., Clees, T., 2010. Advanced Mode Analysis for Crash Simulation Results, 9th LS-DYNA Forum. Bamberg.

Verein Deutscher Ingenieure, 2021. VDI 2206: Development of mechatronic and cyber-physical systems. Beuth, Berlin.

Verein Deutscher Ingenieure, 2019. VDI 2221: Design of technical products and systems – Model of product design. Beuth, Berlin.

Wach, J.J., 1993. Problemspezifische Hilfsmittel für die integrierte Produktentwicklung (Doctoral dissertation). Technical University of Munich, Munich.

Wilmsen, M., 2022. Approach for the development of target-process module sets for the instantiation and configuration of target-process suggestions in the automotive predevelopment (Doctoral dissertation). Karlsruhe Institute of Technology, Karlsruhe.

World Health Organization, 2023. https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries (accessed 27.11.2023).

Zanker, W., 1999. Situative Anpassung und Neukombination von Entwicklungsmethoden. (Doctoral dissertation). Technical University of Munich, Munich.

Zhang, Z., Wang, Y., Jimack, P.K., Wang, H., 2020. MeshingNet: A New Mesh Generation Method Based on Deep Learning, in: Computational Science – ICCS 2020: 20th International Conference, Amsterdam, Netherlands, June 3–5, 2020, Proceedings, Part III. Springer-Verlag, Berlin, Heidelberg, pp. 186–198.

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