

# Augmenting software engineering with AI and developing it further towards AI-assisted model-driven software engineering

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## Abstract

The effectiveness of model-driven software engineering (MDSE) has been successfully demonstrated in the context of complex software; however, it has not been widely adopted due to the requisite efforts associated with model development and maintenance, as well as the specific modelling competencies required for MDSE. Concurrently, artificial intelligence (AI) methods, particularly deep learning methods, have demonstrated considerable abilities when applied to the huge code bases accessible on open-source coding platforms. The so-called big code provides the basis for significant advances in empirical software engineering, as well as in the automation of coding processes and improvements in software quality with the use of AI. The objective of this paper is to facilitate a synthesis between these two significant domains of software engineering (SE), namely models and AI in SE. The paper provides an overview of the current state of AI-augmented software engineering and develops a corresponding taxonomy, *ai4se*. In light of the aforementioned considerations, a vision of AI-assisted big models in SE is put forth, with the aim of capitalising on the advantages inherent to both approaches in the context of software development. Finally, the pair modelling paradigm is proposed for adoption by the MDSE industry.

**Keywords:** Software Engineering, Model-Driven Engineering, Modelling, Domain Modelling, Artificial Intelligence, Big Models, *ai4se*

# 1 Introduction

"In 12 months, we may be in a world where AI is writing essentially all of the code."  
Dario Amodei, CEO Anthropic, Mar. 10, 2025

The advent of artificial intelligence (AI), and more specifically, generative AI, has precipitated a substantial transformation in the field of software engineering (SE), which is expected to undergo further significant changes in the near future (see also the quotation by Dario Amodei, Anthropic). In order to better understand and comprehend these developments, this paper analyses the state of art in using AI for SE. Software engineering is a field of computer science that addresses the development and analysis of systematic approaches for the design, development, verification, validation, and maintenance of software and of software-based systems<sup>1</sup>. It establishes principles and identifies optimal practices for the production and operation of software, with the aim of ensuring the reliability, security, scalability, maintainability and alignment of software with user, business and societal requirements. The objective of software engineering is the production of high-quality software that is cost-effective, delivered in a timely manner and can be readily adapted as requirements evolve.

The term software engineering was coined in 1968 with the very first software crisis ([Valdez, 1988](#)), but still software engineering practices and the resulting software quality have not kept pace with the quality levels required in critical domains or application contexts. In 2024, another dramatic story was added to the software horror show: The millions of enterprise outages caused worldwide by the CrowdStrike Falcon sensor update ([CrowdStrike, 2024](#)) were due to errors such as failing to validate the number of fields in an IPC template type, omitting a runtime array bounds check, a logic error in the content validator and insufficient testing of template types and template instances within the content interpreter. Such software development, which ignores the state of the art in SE, can be described as deficient, if not unprofessional. Software failures are only one indication that SE still lacks comprehensive solutions to the challenges posed by the increasing complexity of software-based systems and the diverse requirements placed on them. The sheer number of software defects, as discussed in ([Shah et al., 2012](#)), also serves as an indicator. This raises the question of whether AI can not only be a very useful tool for SE, but can also contribute to promoting the latest SE research results, for example for MDSE.

This paper therefore discusses the current state of AI applications in SE, how various approaches can be categorised and connected, and how AI could help implement MDSE to further improve software quality: Already ([Brooks and Bullet, 1987](#)) argued that the greatest challenge in software development lies in the specification, design and testing of complex systems, rather than in the work involved in representing the system as code. It emphasized the distinction between essential difficulties (inherent complexity) and accidental difficulties (extraneous challenges), stating that past advances, like high-level programming languages, have only reduced the latter. The paper suggested that addressing accidental difficulties would not lead to major

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<sup>1</sup>In this paper, the term "software" will be used as a general reference to the collective term for computer programs and related SE artefacts.

improvements in software development, as essential difficulties remain fundamental. (Fraser et al., 2007) critiqued the notion of "accidental difficulties", arguing that these so-called accidents are often the result of negligence or poor practices, not mere happenstance. This paper advocated for a disciplined, science-based, and model-driven approach to software development, similar to traditional engineering disciplines.

In model-driven development (MDD (Selic, 2003)), also known as model-driven software engineering (MDSE (Schieferdecker, 2024)), models are original artefacts that are engineered with the intention of facilitating the top-down construction of complex software. Furthermore, models are utilised during runtime to enable the monitoring, verification, and validation of software operations, as well as the optimisation of its performance (Hailpern and Tarr, 2006; France and Rumpe, 2007; Weißleder and Lackner, 2013). The core idea behind using models in SE is to exploit their abstraction and comprehensibility. In theory, models should be easier to develop, use, document and maintain. If code could be fully generated from models automatically, work could be done solely at the modelling level. However, several studies have analysed issues with MDSE, including the integration of generated and hand-written code, the modularity of the generated code, and the organisation of the development process (see (France et al., 2013), for example).

In another line of research and development, AI techniques have been employed in software engineering activities from the outset, see for example (Barstow, 1988). Against the backdrop of significant advances in AI-assisted software development, (Burke et al., 2021) predicted that it would reach the peak of inflated expectations within five to ten years, after which it would enter a phase of productivity stabilisation. Subsequently, (Chandrasekaran and Davis, 2023) estimated that AI-assisted software development would reach the productivity plateau within just two to five years. The ongoing increase in demand for software, driven by the global shift towards digitalisation, can be met by utilising AI solutions in software engineering. Despite the support of AI, software engineering continues to be important for the development of high-quality, fit-for-purpose software. The focus is on augmentation, not replacement, of software engineers.

Therefore, this paper investigates the intersection of AI and SE, specifically MDSE, to improve software engineering practices. The paper aims to bridge the gap between the theoretical advantages of MDSE and its practical limitations by integrating AI techniques. It introduces a novel taxonomy, *ai4se*, which classifies research on AI methods within the SE domain, as well as the more specific MDSE domain. The paper draws on a literature review and an analysis of SE practices and AI applications to develop the taxonomy. The main contributions of the paper include:

- The new **AI in Software Engineering Taxonomy *ai4se***. This taxonomy categorises AI applications based on the purpose of applying AI, the target of AI within SE such as requirements engineering or the testing process, the type of AI used, and the level of autonomy achieved by the AI.
- The new **Model Naturalness Hypothesis**, which posits that models have statistical properties that can be used to develop more effective software engineering tools.

- The new concept of **Big Models**, analogous to big code, as a basis for advanced empirical MDSE. The paper suggests that these models can be generated top-down, or extracted bottom-up from code, and that AI methods can be applied to these big models.
- The renewed paradigm of **pair modelling** in AI-augmented MDSE involves a software engineer and an AI tool/agent collaborating on software development in a manner similar to pair programming. The aim is to combine the strengths of humans and AI to improve the quality of software and enable the immediate consideration of ethical issues in MDSE.

The *ai4se* taxonomy is validated by categorising highly cited and recent publications in AI-augmented SE. This classification shows the various ways AI is being applied across different activities in SE, such as requirements engineering, architecture design, coding, testing, and deployment.

Section 2 discusses the availability of large code sets on coding platforms that form the basis for training AI using actively applied, operated and maintained code. Section 3 addresses the role of models in SE. Bringing these two sections together, Section 4 discusses the utilisation of AI for SE. This section presents the taxonomy of AI for SE *ai4se*, which has been developed to facilitate a deeper understanding of this evolving field. Finally, Section 5 discusses the adoption of MDSE practices with the help of AI. This section examines recent developments in AI-augmented modelling and model utilisation within SE, presenting the big model concept and the pair modelling paradigm in AI-augmented MDSE. Section 4 reviews related work. The paper concludes with a summary and outlook.

## 2 Big Code in Software Engineering

The online availability of open-source software (OSS) paved the way for software reuse. It has also transformed the landscape of software licences and the way software is developed, with developers using OSS for specific components or entire products. OSS has also enabled deeper insights into software architecture and development practices. It has enabled new approaches to empirical software engineering, deepening our understanding of SE.

The advent of software coding platforms can be traced back to the 1990s, although it was not until the early 2000s that they truly gained prominence, with the launch of GitHub in April 2008 representing a significant milestone in this regard. At the present time, GitHub is the most widely utilised software coding platform. As stated by ([Blog, 2021](#)), GitHub hosts over 100 million projects and 40 million users. It became not only a significant platform for software engineering collaboration, but also a prominent reference for open-source software mining ([Kalliamvakou et al., 2014](#)). The study also demonstrated that a considerable number of GitHub repositories are not directly related to software development. This is because GitHub is not solely utilised for coding collaborations; it is also employed for collaborations on websites, editing books or other publications, and is even used as a storage platform. A later manual analysis by the same authors ([Kalliamvakou et al., 2016](#)) revealed that over a third of the repositories on GitHub were not software development repositories. According to ([Apache,](#)

2025), code repositories constitute around 20% of the lines stored on GitHub (see Figure 2a).

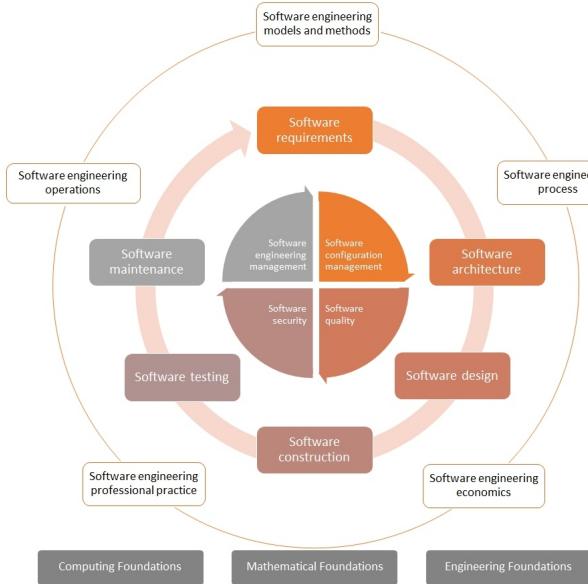
As the vast quantities of software code have accumulated over time, the term "Big Code" has evolved (see, for example, (Markovtsev and Long, 2018; Ortin et al., 2016; Vechev et al., 2016)): Not only can the available code be reused, extended and analysed, it can also be used to train ML models, enabling the application of AI for SE on a large scale (Li et al., 2023). The term big code signals a fundamental shift in the analysis and construction of software, moving from a focus on the formal logic of a single program to identifying statistical patterns within vast repositories of source code. (Allamanis et al., 2014) considered the statistical properties of code to be similar to those of natural language, meaning code is full of learnable, predictable patterns. This observation later led to the formulation of the naturalness hypothesis (Allamanis et al., 2017).

### 3 Models in Software Engineering

According to the IEEE Software Engineering Body of Knowledge (Society, 2024) (see Figure 1), the software lifecycle is comprised of distinct phases and activities that can be described as knowledge areas, including requirements, architecture, design, construction, testing, and maintenance. There are also knowledge areas that deal with the fundamentals of computer science, mathematics, and engineering, as well as cross-cutting activities pertaining to software quality, security, configuration management, and engineering management. Furthermore, there are cross-cutting knowledge areas that encompass the processes, operations, professional practice, and economics of software engineering, along with a distinct area for software engineering models and methods. This knowledge area encompasses the processes and methodologies associated with modelling, the various types of models, including those pertaining to information, behaviour, and structure, and the analysis of models, see also (Schieferdecker, 2024). Overall, SWEBOk addresses dedicated model-based and model-driven approaches in each knowledge area, such as model-based requirements specification, model-based architecture, model-driven design, lifecycle models, executable models, model-based testing, etc.

This is because models in SE are the key to dealing with the complexity of software: Models provide the essential abstractions to capture requirements, support design decisions, or to offer comprehensive overviews of software structures and behaviours. They are essential tools in the engineering process for constructing and maintaining software. They are also vital for configuration, monitoring, and runtime support during software operation and management.

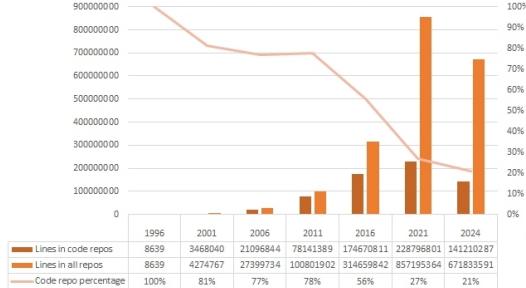
However, the adoption of MDSE in the industrial practice remains limited. (Alfraihi and Lano, 2023) reports that, in this survey, only 37.4% of the participants stated that "MD[S]E is used in most projects and by most developer", while 46% reported limited or no use. Nowadays, however, MDSE does not only rely on models in the Unified Modelling Language (UML), in other standardized modelling languages, such as Business Process Modelling Language (BPMN), or in Domain-Specific Languages (DSL): Rather than explicitly developing software models and using them from the top



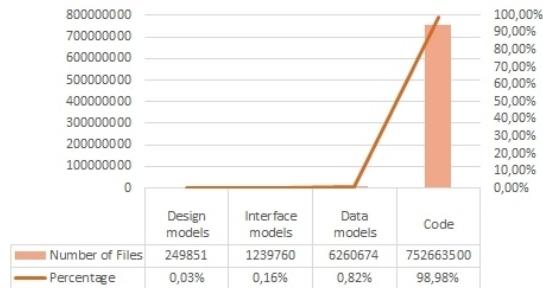
**Fig. 1:** Software Engineering knowledge areas according to SWEBOk ([Society, 2024](#))

down, they can be extracted from software executions, monitoring, or static analysis. These approaches aim to minimise the costs associated with model development while still reaping the benefits of MDSE ([Bagheri and Sullivan, 2013](#)). The combination of explicitly developing model artefacts and extracting models from code artefacts has resulted in a hybrid top-down/bottom-up MDSE approach, as described in ([Steffen et al., 2007](#)). This approach benefits from both directions of MDSE, as demonstrated in ([Vaupel et al., 2015](#); [WeiBleder and Lackner, 2013](#); [Garcia et al., 2023](#)). Furthermore, as large volumes of data are interpreted more dynamically depending on their current application context, new data modelling approaches have evolved ([Ribeiro et al., 2015](#)). Examples include Not Only SQL (NoSQL), JavaScript Object Notation (JSON), Resource Description Framework (RDF), and Yet Another Markup Language (YAML).

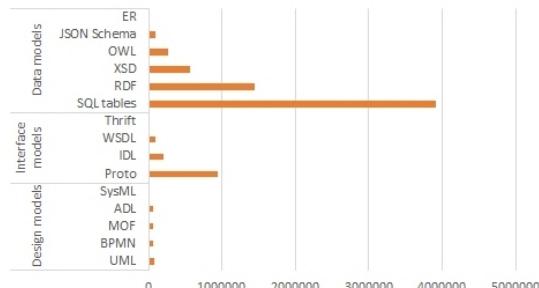
The formal structures of models, together with the increased use of advanced data models and the bottom-up and hybrid modelling approaches, have paved the way for MDSE with AI by making larger model sets available for AI training. Additionally, machine learning is employed to render models suitable for further processing, even when they are not inherently machine-processable, as with images: ([Shcherban et al., 2021](#)) presents an approach to automatically detecting images containing one or more of the ten types of UML diagrams being analysed. This approach was used to derive a larger model set containing these ten types of UML diagrams. It complements other approaches for providing ground truth model sets, such as the Lindholmen model set ([Robles et al., 2017, 2023](#)), which includes 'almost 100k models from 22k [GitHub] projects', and the ModelSet ([López et al., 2022](#)).



(a) Lines and portion of GitHub code repositories



(b) Number and percentage of GitHub files in code repositories



(c) Number of modelling files in code repositories

**Fig. 2:** Repositories breakdown by Kibble and GitHub search taken 4-6 February 2025

An analysis using the GitHub search API indicates that around 1% of GitHub files contain models or partial model information. Counting the number of code and model files in GitHub repositories reveals the ratio of code to model files for software designs, interface models, and data models (see Figure 2b). Figure 2c shows the split between design, interface and data models. These figures are only rough indicators. Lines of code and the number of files are crude measures of software. File extensions do not accurately indicate file types. Furthermore, there are numerous coding and modelling tools, some of which have proprietary file extensions. Images are not counted.

Nevertheless, the analysis showing a low number of modelling files on GitHub is consistent with the analysis of (France et al., 2013) from over a decade ago. The authors of this study argue that, while code generators can produce large amounts of code, not all of it is necessarily useful or would have been written manually. The effort required to develop, maintain and adapt the generators offsets the productivity gains from modelling. Manual code changes make round-trip engineering difficult. Generated code must be checked by developers to ensure correctness, which limits the benefits of automation. Also, poor software design models can lead to inefficient development. Consequently, developers often prefer generic solutions with hand-written, reusable code to customised, generated solutions. Furthermore, as programming languages and frameworks become more expressive, the need for model-driven code generation would diminish. However, while generative AI can empower software developers further, it also makes MDSE more practical and applicable to a wider range of software projects. The ability to regenerate models from code and/or keep them in sync with evolving software requirements and manual code changes addresses the limitations of MDSE that have been identified thus far. Despite these limitations, the Lindholm dataset and the GitHub analysis demonstrate that MDSE has been used continuously for the aforementioned reasons. However, the GitHub analysis also reveals that modelling is currently predominantly employed for data and interface structures, as robust functionality of these elements hinges on a well-defined structure (see, for instance, (CrowdStrike, 2024)). The analysis also shows that design and behaviour models for software projects are rarely used.

## 4 Artificial Intelligence in Software Engineering

Big code (see Section 2) constitutes the basis to train AI in recognising coding patterns and anti-patterns. These are now accessible via AI tools that can complete code, detect defects, summarise code, translate code, enhance code searches, and check and learn coding conventions, among other things. The potential of using AI for SE was discussed as early as 1988 in (Barstow, 1988), and has been a topic of discussion ever since, most recently for instance in (Alenezi and Akour, 2025). For example, (Feldt et al., 2018) proposes the AI in SE Application Levels (AI-SEAL) taxonomy, which differentiates between the point of applying AI to the software engineering process, the software product or at runtime, the levels of automation, and the types of AI along the five tribes differentiation by (Domingos, 2015). It is noteworthy that the majority of the papers analysed in (Feldt et al., 2018) employ AI in the software engineering process. However, despite the numerous facets of the software engineering process (see Figure 1), this study does not provide further elaboration. Nevertheless, other publications offer more detailed discussions of AI in SE, including (Barenkamp et al., 2020) or (Ozkaya, 2023), see also Section 6. Notwithstanding the aforementioned considerations, a taxonomy for the role of AI in software engineering has yet to emerge.

In light of the recent advancements in machine learning (ML), in particular in deep learning (DL), that have made significant breakthroughs possible, this paper focuses mainly on the latest developments in the application of ML to SE. For ML

to be effective, it is essential to utilise the appropriate structures inherent to SE artefacts, which has been a topic of considerable debate: (Allamanis et al., 2017) presents an overview of the various ways in which source code can be represented, including representational models of tokens, token contexts, program dependency graphs, API calls, abstract syntax trees, object usage, and others. These representational models are used for AI assistance in SE, including the creation of recommender systems, the inference of coding conventions, the detection of anomalies and defects, the analysis of code, the rewriting and translation of code, the conversion of code to text for the purposes of documentation and information retrieval, and the synthesis and general generation of code from text. (Karampatsis et al., 2020) adds further applications of AI assistance such as code completion, API migration and code repair. Furthermore, (Allamanis et al., 2017) presents "[t]he naturalness hypothesis[:] Software is a form of human communication; software corpora have similar statistical properties to natural language corpora; and these properties can be exploited to build better software engineering tools.". Given the intrinsic formats and formal characteristics of coding and modelling languages employed in SE, the second aspect of the naturalness hypothesis can be considered relatively straightforward. Yet, the initial proposition reinforces the necessity for SE artefacts that are readily comprehensible. This assertion was previously made by (Fowler, 2005) in a different form: "[A]ny fool can write code that a computer can understand, good programmers write code that humans can understand.". Consequently, the application of AI in SE is not merely concerned with code generation or code repair; it also encompasses the enhancement of code through techniques such as refactoring, with the objective of optimising readability and maintainability.

So, while a vast amount of approaches to utilising AI in SE have emerged in the scientific literature, they can be broadly categorised into three principal lines of enquiry: supporting the understanding of SE artefacts, the generation of SE artefacts from another, and the improvement of SE artefacts. These principal approaches may be applied to a variety of SE artefacts, including, but not limited to, requirements, designs, codes, tests, builds and/or miscellaneous of SE processes.

The *ai4se* taxonomy was inspired by numerous discussions concerning the application of AI in the field of SE. In the absence of a taxonomy that addressed the various options and intricacies of SE and/or AI, a new taxonomy was developed, drawing inspiration from other surveys (see Section 6). The dimensions of the first level of *ai4se* are categorised as follows: (1) the **purpose** of using AI for software engineering, (2) the **target** of using AI within software engineering, (3) the **type** of AI used, and (4) the **level** of autonomy/automation achieved by the AI.

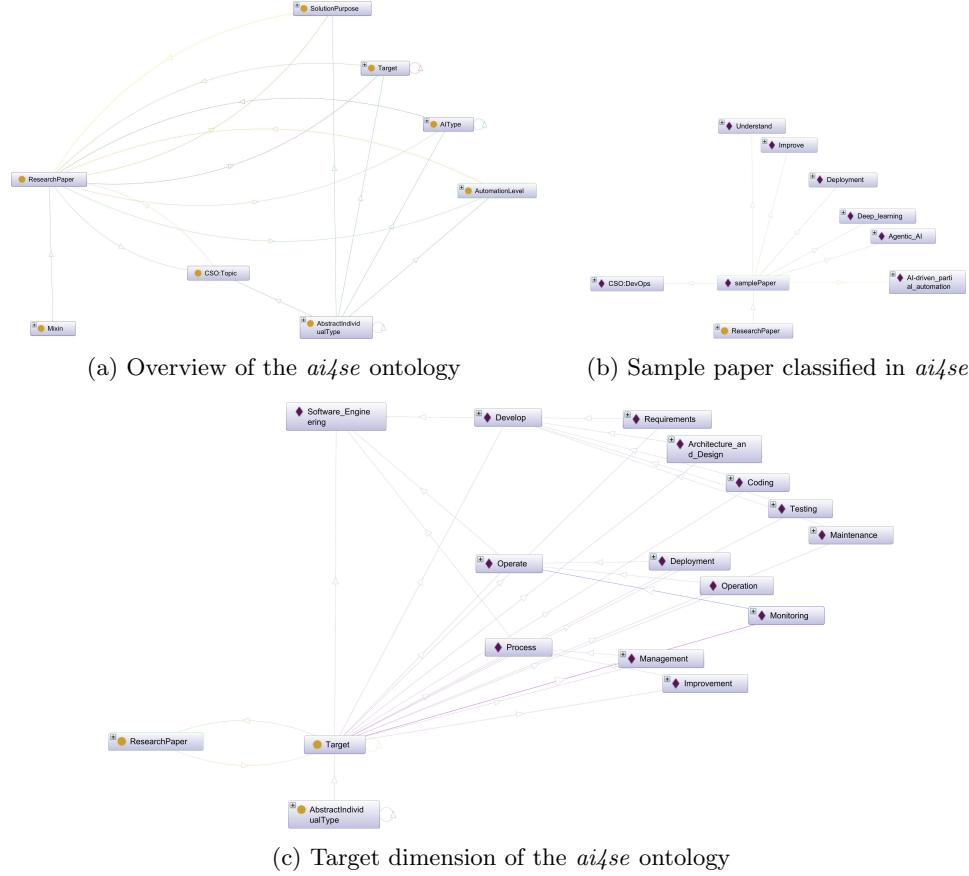
The **purpose** dimension has the three facets of (P1) **understanding** to gain insight, (P2) **generating** to derive (parts of), and (P3) **improving** to refine SE artefacts and/or SE processing. An approach may address multiple purposes. If it is **hybrid** in this sense, all its purposes are made explicit, e.g. to support understanding only is denoted by 'P1', or to support both understanding and generation is denoted by 'P1, P2'.

The *ai4se* application **targets** consist of the main SE activities as described by SWEBOk (Society, 2024) and DevOps (Kumar et al., 2024): (S1) Software **development** includes requirements engineering, architecture and design, coding, testing, and maintenance. (S2) Software **operations** includes deployment, operation, and monitoring. Together with the (S3) SE process including management and improvement, the three form the target of application dimension in the taxonomy. Each of the target options can be performed with the support of models, based on models or even driven by models, or without them. For the sake of comprehension of the taxonomy, the **model** option is optional for each application target: If models are used, i.e. the application target is MDSE, it is marked with "(m)". Thus, the application target "S1.m" refers to software development with models, and "S1" to one without. Or, in a more fine-grained analysis, "S1.d.m" would be used for model-based testing and "S1.d" for testing without models. An approach may address several application targets. If it is **hybrid** in this sense, all of its goals can be made explicit, e.g. support for coding only is denoted by "S1.c", support for both coding and testing is denoted by "S1.c, S1.d", or support for coding and model-based testing is denoted by "S1.c, S1.d.m". For simplicity, "h" can also be used to indicate a hybrid approach of several targets.

The **types** of AI are divided into (T1) **symbolic** AI, i.e. knowledge representation, rule-based systems, and logical reasoning, (T2) being **subsymbolic** including **statistical** AI, i.e. probabilistic modelling and inference, Bayesian networks, Markov models, Gaussian processes, etc., **classical machine learning**, i.e. supervised, unsupervised, and reinforcement learning, feature engineering and selection, etc., and **deep learning**, i.e. neural networks, transformers, transfer learning, self-supervised learning, attention mechanisms, etc., (T3) **generative AI** (GenAI), i.e. large language models (LLM), generative adversarial networks, diffusion models, variational autoencoders, autoregressive models, contrastive learning, reinforcement learning from human feedback, etc., (T4) **agentic AI**, i.e. multi-agent systems, planning and decision making, hierarchical reinforcement learning, etc., and (T5) **general purpose AI**, i.e. meta-learning and world models. Today, all types (T1) to (T5) are used in software engineering, but not (T5) due to its non-existence. An approach can also use a combination of AI types, i.e. it can be **hybrid**. This can be made explicit, e.g. by denoting "T1, T2" for a hybrid approach that uses both symbolic and classical machine learning. For simplicity, "h" can just be used to denote a hybrid approach that uses more than one type of AI.

The **levels** of autonomy/automation are defined similarly to the levels of autonomous driving (Barabas et al., 2017) as five levels from no support to recommendations to full automation: (L0) **No** AI-assisted automation, (L1) AI-assisted **options**, where the developer is in full control and receives recommendations to choose from and adapt, (L2) AI-assisted **selection**, where the AI selects pre-defined options, (L3) AI-based **partial automation**, where the AI selects options in simple, standard cases, and (L4) AI-based **full automation**, where the AI operates without the developer. So far, level L1 and L2 are the most common, level L3 is on the rise and level L4 is rather unrealistic for complex, industrial-scale software. Higher levels of autonomy

typically include the capabilities of lower levels of autonomy; when presenting the level of autonomy of an approach, the highest level of autonomy is given.



**Fig. 3:** The *ai4se* taxonomy defined as an ontology

To define this taxonomy more formally, the Web Ontology Language (OWL) (McGuinness et al., 2004) was used, due to its association with the Semantic Web and the support offered by the Protégé tool (Musen, 2015) (see Figure 3). The *ai4se* ontology definition is based on gUFO (Almeida et al., 2019) as a grounding and uses, in addition, the Computer Science Ontology (CSO (Salatino et al., 2020)) to associate a general research topic with a research paper. A research paper itself is an endurant and the dimensions used to classify its research contribution are abstract individual types. However, as the ontology lends itself to interactive elaboration rather than graphical representation, this paper uses a different tabular representation to depict the classification of the research papers, as shown in Figure 4. Interested readers can, however, explore the classification of research papers directly in the ontology (Schieferdecker,

2025), to which they can also contribute. The *ai4se* ontology can be used not only to understand the concepts in the research field of AI for SE better, but also to explore research related to a specific aspect, such as all papers on agentic AI for SE, using SPARQL queries as shown in Listing 1 and 2<sup>2</sup>. *ai4se* has been defined as an ontology because, although taxonomies have been proposed for every area of SE knowledge within the SWEBOK (Society, 2024) as discussed in (Usman et al., 2017), neither SWEBOK nor any other source defines a comprehensive SE ontology that could be used to classify research results for the purpose of this paper. For example, while the CSO is quite detailed, it does not cover the knowledge areas of SWEBOK. For example, it lacks the concept of 'runtime monitoring' of software components and includes 'object-oriented design' at the top level, even though this is just one type of software design.

```

1 PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
2 PREFIX ai4se: <http://purl.org/ai4se/ontology#>
3 SELECT ?paper
4 WHERE {
5   ?paper ai4se:hasLevel ai4se:AI-assisted_options .
6 }
```

Listing 1: All papers on AI-assisted options automation.

```

1 PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
2 PREFIX ai4se: <http://purl.org/ai4se/ontology#>
3 SELECT DISTINCT ?target
4 WHERE {
5   ?paper rdf:type ai4se:ResearchPaper .
6   ?paper ai4se:hasTarget ?target .
7 }
```

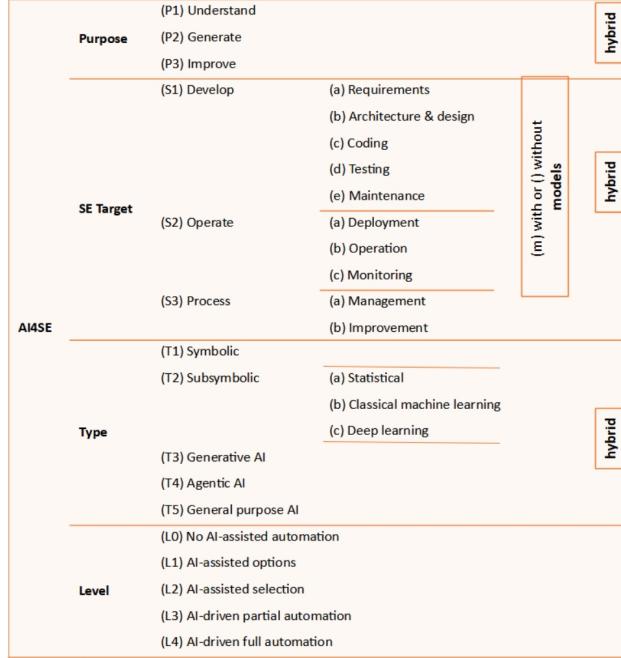
Listing 2: All software engineering targets addressed by research papers.

The fidelity of the new taxonomy *ai4se* (Figure 4) is verified by reviewing and classifying highly cited publications, but also recent publications to demonstrate the applicability of this taxonomy. A lightweight systematic literature review (SLR), as described in (Stapic et al., 2012), was conducted to analyse related research. This SLR protocol was followed:

- **Review title:** SLR on evaluating the status of AI for SE research by applying the *ai4se* taxonomy.
- **Objectives of the review:**
  1. To determine research on AI for SE
  2. To test the validity of the *ai4se* taxonomy with a research selection.
  3. To determine a classification of the selected research.
- **Research questions:**
  - RQ1: What is the current status of research on AI for SE and for MDSE?
  - RQ2: Are the dimensions of the *ai4se* taxonomy suitable for classifying current AI for SE research results?
  - RQ3: Are all dimensions and facets of the taxonomy represented in research work?

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<sup>2</sup>SPARQL is the standard query language and protocol for linked open data on the Web as defined by RDF triples. The OWL ontology *ai4se* is already encoded in RDF triples, making it immediately queryable with SPARQL.



**Fig. 4:** Overview of the *ai4se* taxonomy

- RQ4: What are typical purposes addressed, targets tackled, types used, and levels of automation with AI reached?
- **Database:** An automated search on dblp, ACM DL, and IEEE Xplore of SE and AI related research papers published between 2020 and 2025. Snowballing extension of the search results with Research Rabbit, Citation Gecko, and Google Scholar. Consolidation of the search results with Zotero.
- **Inclusion criteria:**
  - Original research papers in English.
  - Online available.
  - Research on AI for SE.
- **Exclusion criteria:**
  - Research on SE for AI.
- **Selection process:**
  1. Title and abstract screening for the pre-selection of unique research candidates by use of the concept map resulting from the *ai4se* ontology including synonyms.
  2. Full text review and assessment of the research contributions for the final selection of unique research.
  3. Tools: Python for text analysis and post-processing of finally selected research, supported by MS Visual Studio, Google AI Studio, and LibreOffice.
- **Synthesis process:**
  - Review of the finally selected research and inclusion in the *ai4se* ontology.

Paper	Summary	Purpose	Target	Type	Level
(Lin et al., 2021)	T-BERT generates trace links between source code and natural language artefacts. It represents a significant advancement in automated software traceability, offering improved accuracy, efficiency, and practicality.	P2	S1	T2.c	L3
(Körner et al., 2014)	Natural language processing (NLP) approach for improving requirements engineering in the automotive industry: It identifies flaws, such as ambiguous words, incomplete process descriptions, or incorrect quantifiers.	P3	S1.a	T1	L2
(Perini et al., 2012)	CBRank method for prioritising software requirements: It uses stakeholder input and requirement attributes to generate an optimal ranking and enables adaptive elicitation by refining the prioritisation based on real-time feedback.	P3	S1.a, S2.a, S3.a	T1, T2.b	L2
(Bhat et al., 2019)	ADeX is a tool designed to automate the curation of architectural design decisions in software development. It helps automate the management of architectural decisions, reducing documentation effort while improving decision accuracy.	P1, P3	S1.b, S2.a	T1, T2.b	L3
(Bird et al., 2023)	Explores the early experiences of developers using the AI-augmented coding assistant GitHub Copilot. It may expand to debugging, code review, and software maintenance, requiring better trust and provenance tracking.	P1, P2	S1.c	T3	L3
(Svyatkovskiy et al., 2020)	IntelliCode Compose is a code completion tool that uses a generative transformer model to predict sequences of code tokens, including entire lines of code. It has been trained on a massive dataset of 1.2 billion lines of code across multiple programming languages.	P2, P3	S1.c	T2.a, T2.c, T3	L3
(Bader et al., 2019)	Getafix is an automated bug-fixing tool that learns from past, human-written fixes to suggest human-like fixes for static analysis warnings.	P2, P3	S1.c, S1.d	T2.a, T2.b	L2
(Guo et al., 2020)	GraphCodeBERT improves code understanding by incorporating dataflow graphs into the BERT transformer architecture. Data flow graphs represent dependencies between code variables and improve semantic understanding over treating code as a simple sequence of tokens.	P1	S1.c, S1.d, S1.e	T2	L1
(Gupta and Sundaresan, 2018)	DeepCodeReviewer is an automatic code analysis system that learns from historical peer reviews to identify and suggest relevant reviews for code snippets.	P1, P3	S1.c, S1.d	T2	L2
(Drain et al., 2021)	Introduces DeepDebug or automated bug detection and fixing in Java: It generates non-deletion fixes that modify instead of just deleting code	P1, P2	S1.c, S1.e	T3	L3
(Tufano et al., 2022)	Approach improves code review automation with DL by working with pre-trained models on raw source code and English text.	P1	S1.c, S1.d	T3	L2
(Tatineni, 2024)	The book discusses the application of AI beside others for infrastructure monitoring and anomaly detection, predictive maintenance, and build pipeline optimization.	P1, P3	S1.c, S1.d, S2.a, S3.b	T2.a, T2.b	L3
(Bouzenia et al., 2025)	Presents RepairAgent for automated program repair that allows to autonomously plan and execute actions, such as gathering information, searching for code snippets, and validating fixes, by interacting with a set of specifically designed tools.	P3	S1.c, S2.a	T4	L3
(Lenz et al., 2013)	Approach links different types of testing information to help automate the generation of equivalence classes for testing. The linking supports tasks such as test reduction, prioritisation and selection.	P1, P2, P3	S1.d	T2.a, T2.b	L2
(Zhao et al., 2015)	Presents a hybrid approach to test case prioritization for regression testing aiming to minimise testing costs. Aims to enhance software testing efficiency by optimising test case execution order.	P3	S1.d, S1.e	T1, T2.a, T2.b	L2
(Spieker et al., 2017)	Introduces Retees for automatic test case prioritisation and selection in continuous integration. It uses test case meta-data to adapt to changes in the environment and prioritise error-prone test cases.	P3	S1.d, S2.a	T2.b, T2.c	L3
(Ceran et al., 2023)	Explores machine learning-based ensemble methods to predict software quality more accurately than previous approaches	P1	S1	T2.b	L3

Table 1: AI-assisted software engineering (sorted by application targets)

A total of 229 studies on AI for SE were identified. Of these, 32 were primarily SLRs, 46 papers described (elements of) research roadmaps for (aspects of) AI for

SE, and 10 papers presented taxonomies for (aspects of) AI for SE. Twelve SLRs, eight roadmaps and seven taxonomies are summarised and compared in Tables 3, 4 and 5 respectively, due to their relation to the *ai4se* taxonomy. A further 82 papers present original methods, techniques, and tools for AI for SE excluding AI for MDSE. Of these, 17 were finally selected and classified as shown in Table 1. For research on AI for MDSE, see Section 5 for details of the 16 research papers selected from a total of 59 research items on AI for MDSE. Please note that the SLR results are available online, and that the *ai4se* taxonomy will be extended in the future to include further original research papers.

The selected original research on AI for SE in general is presented in Table 1. Additional details are given here: For **requirements**, (Körner et al., 2014) presents an AI-based automation approach to requirements engineering that begins by converting natural language into an Eclipse Modelling Framework (EMF) model. It then applies linguistic rules to identify errors, such as ambiguities or incorrect quantifiers, and provides suggestions for requirements analysts to make final decisions. This approach supports the entire requirements elicitation and change process. Another **requirements improvement** is given in (Perini et al., 2012) presenting the prioritisation of requirements by combining the preferences of project stakeholders with approximations of the order of requirements computed by ML techniques.

For **architecture and design**, (Bhat et al., 2019) describes the automated curation of design decisions to support architectural decision-making. It helps software architects by organizing and recommending design decisions based on previous cases and contextual information of the current project. By leveraging existing design knowledge, the approach analyses historical data and design choices to improve the quality and consistency of architectural designs.

The list of publications on AI-assisted **coding**, **testing**, and **maintenance** is huge. Major developments are for example described in (Gupta and Sundaresan, 2018) for **code understanding**. It introduces DeepCodeReviewer that uses deep learning to recommend code reviews for common issues based on historical peer reviews. It assesses the relevance of reviews to specific code snippets, suggests appropriate reviews from a repository of common feedback, and improves code reviews by focusing on defect detection. (Guo et al., 2020) describes GraphCodeBERT, a pre-trained model for programming languages that incorporates data flow semantics rather than just code syntax. GraphCodeBERT demonstrates its performance both in code understanding for code search and clone detection, and in code generation and improvement through code translation and code refinement. (Ceran et al., 2023) presents a study focused on predicting software quality using defect density as a key feature representing quality to achieve higher accuracy in software quality prediction compared to previous studies. The research shows that data pre-processing, feature extraction and the application of ML algorithms significantly improve prediction accuracy. (Bird et al., 2023) discusses early experiences of developers using GitHub Copilot, which uses a language model trained on source code. Guided by Copilot, developers can write code faster than a human colleague, potentially accelerating development. Three empirical studies with Copilot highlight the different ways developers use Copilot, the challenges they face, the evolving role of code review, and the potential impact of pair programming with AI

on software development. (Svyatkovskiy et al., 2020) discusses IntelliCode Compose, a multilingual code completion tool that predicts entire sequences of code tokens up to full lines of code. The generative transformer model has been trained on 1.2 billion lines of Python, C#, JavaScript and TypeScript code. (Bader et al., 2019) presents Getafix, a tool for fixing common bugs by learning from previous human-written fixes. It uses hierarchical clustering to group bug fix patterns into a hierarchy from general to specific, and a ranking system based on the context of the code change to suggest the most appropriate fix. Another debugging approach, DeepDebug, is presented in (Drain et al., 2021), which has been trained by mining GitHub repositories to detect and fix bugs in Java methods.

Since different software **testing** techniques are complementary, reveal different types of defects and test different aspects of a program, (Lenz et al., 2013) presents an ML-based approach to link test results from different techniques, to cluster test data based on functional similarities, and to generate classifiers according to test objectives, which can be used for test case selection and prioritisation. (Tufano et al., 2022) discusses a test generation approach for writing unit test cases by generating assert statements. The approach uses a transformer model that was first pre-trained on an English text corpus, further semi-supervisedly trained on a large source code corpus, and finally fine-tuned for the task of generating assert statements for unit tests. The assert statements are accurate and increase test coverage. (Zhao et al., 2015) discusses test case prioritisation based on source code changes, software quality metrics, test coverage data, and code coverage-based clustering. It reduces the impact of similar test cases covering the same code and improves fault detection performance.

For *deployments*, (Tatineni, 2024) explores the role of ML in DevOps for intelligent release management. It suggests besides other things combining continuous monitoring, predictions of the likelihood of deployment failures, root cause analysis, and pipeline optimisation to reduce deployment failures and improve release management efficiency and software quality.

For the SE **process**, (Spieker et al., 2017) introduces Retecs, a method for automatically learning test case selection and prioritisation in continuous integration, aimed at minimising the time between code commits and developer feedback on failed tests. Retecs uses reinforcement learning to select and prioritise test cases based on their execution time, previous execution history and failure rates. It effectively learns to prioritise error-prone test cases by following a reward function and analysing past CI cycles. (Lin et al., 2021) presents the T-BERT framework for generating trace links between source code and natural language artefacts such as requirements or code issues. It demonstrates superior accuracy and efficiency for software traceability, especially in data-limited environments.

Overall, the majority of the presented selection of recent research focuses on improving the software engineering process, either by improving coding, requirements engineering, testing, or the overall processes. A smaller number of approaches aim to improve the understanding of software engineering artefacts. There are also methods that focus on generating code or code-related content. A mixture of AI types are used, including symbolic, statistical, ML, DL and GenAI, as well as hybrid approaches. Many of the AI approaches offer AI-assisted selection, i.e., they provide suggestions,

recommendations and rankings that can help developers, but require a developer to make the final decision on what to do. AI-based partial automation is also a common level, where tools automate part of the process, but may require a human to review or further integrate the results. On the whole, the dimensions of the *ai4se* taxonomy are adequately covered, although not every possible combination has yet been addressed — it may even be impossible to do so. For example, the prospect of full automation driven by AI using only symbolic AI is unlikely, since the nuances of SE can only be effectively managed with more advanced non-symbolic AI. However, as AI for SE is a very active area of research, further research results will emerge that make use of the open combinations of the taxonomy dimensions. To accommodate these results, the taxonomy is available online ([Schieferdecker, 2025](#)) and will be continuously updated.

## 5 AI-Assisted Model-Driven Software Engineering

The substantial increase in the utilisation of AI for SE, as described in the previous section, is in parallel with a notable rise in the application of AI to MDSE in the following areas: model creation and elicitation; model completion, refinement and repair; intelligent model transformations; model validation and verification; reverse engineering and model discovery; and model-based testing. Using AI in MDSE enables the management of unprecedented complexity, improving the quality and consistency of software projects. These developments can also be explained by the novel 'model naturalness hypothesis', which extends the naturalness hypothesis ([Allamanis et al., 2017](#)) to modelling artefacts in software engineering:

### The model naturalness hypothesis

Software is a form of human communication as well as a form of human-computer communication; **model corpora**, software corpora, and natural language corpora have similar statistical properties; the properties of model corpora can be employed to develop more efficacious software engineering tools.

Readers familiar with software modelling techniques will not be surprised by this hypothesis. Like software code, software models are expressed in (semi-)formally defined languages with precise, often graphical, syntax and semantics. In this respect, software models are similar to software code. However, they are often only used in the initial phases of software design to sketch the desired solution. Consequently, they are used to visualise code and are not stored in a machine-readable format for reuse and further processing. In contrast, however, software models can facilitate human-human and human-computer communication if they are treated as machine-processable, high-level software artefacts rather than images (see also ([Babur et al., 2018](#))). In this case, models can form corpora that can be analysed automatically and used to train AI. The model naturalness hypothesis has therefore been made explicit. Indeed, the

advent of big code and AI has opened up new avenues for integrating AI into model-driven approaches. As demonstrated by (Hamilton et al., 2017), the intrinsic formal graph structures of SE models can also be leveraged to facilitate the preparation of models for gaining AI advantages in MDSE. This is analogous to the considerations in (Pudari and Ernst, 2023) on the necessity to elevate abstraction levels in language models to enhance the efficacy of AI-assisted automated coding.

Foundational work on ground truths for developing and benchmarking AI applications in MDSE is discussed in (Torcal et al., 2024; Shcherban et al., 2021) and (Mangaroliya and Patel, 2020). (Torcal et al., 2024) presents the creation and validation of a new, high-quality ground truth dataset of UML diagrams. The curated dataset of 2626 unique and accurately labelled images across six UML diagram types goes beyond the Lindholmen dataset of modelling artefacts (Robles et al., 2017, 2023). The new ground truth dataset was also presented for an improved approach to UML diagram classification. Also (Shcherban et al., 2021) presents a new dataset of images, manually labelled into four UML diagram types (class, activity, sequence, use case) and a non-UML category, which is used to develop new DL approaches with higher precision to automate UML diagram classification. Another ground truth dataset is described in (Mangaroliya and Patel, 2020).

The selected original research on AI for MDSE is categorized in Table 2. Further details can be found here: The majority of the original work on AI for MDSE is focuses on supporting the design of software: (Babur et al., 2018) was one of the first studies to suggest treating models as data for training LLMs, enabling the application of ML techniques to MDSE.

Another significant area of research concerns the use of AI to improve domain modelling. (Kulkarni et al., 2023) presents a methodology for AI-augmented MDSE as a continuous cycle of AI-generated model proposals by LLMs, which are then reviewed and refined by humans. This approach aims to bridge the gap between the natural language used by domain experts and the formal languages employed in MDSE. (Chen et al., 2023) investigates the feasibility of using LLMs to automate domain modelling in SE. It applies various prompt engineering techniques to a dataset of diverse domain modelling examples and finds that while LLMs show promising domain understanding and achieve relatively high precision in generating classes and attributes, their recall remains low, particularly for relationships. It concludes that full automation is currently impractical. In (Yoo et al., 2022), the presented method, DDA, was shown to enable efficient performance prediction and design variable estimation by generating virtual responses from a small set of actual responses and integrating domain knowledge. When applied to vehicle bumper design, the method produced virtual responses that were approximately 95% similar to real data, outperforming existing metamodels.

(Saini et al., 2022) addresses the question of how to improve the modeller-bot interaction. The bot presented in the study suggests alternative model configurations based on a novel algorithm and updates the domain model based on modeller input. This addresses the limitations of existing automated methods. Evaluations demonstrate high accuracy and rapid performance. (Hartmann et al., 2017) also examines the interaction between the modeller and the AI tool and propose a multistrategy learning

Paper	Summary	Purpose	Target	Type	Level
(Babur et al., 2018)	This paper presents quantitative evidence from academia and industry regarding the increased use of models. It suggests using models as data and applying machine learning techniques to improve our understanding of them.	P1	S1.m	T2.b	L0
(Kulkarni et al., 2023)	Discusses NLP-driven model generation for more efficient model construction. Presents "purposive" meta-models that guide the interactions between domain experts and GenAI to generate effective prompts for model construction.	P2	S1.a.m, S1.b.m	T1, T3	L3
(Chen and Wang, 2024)	Discusses the NLP-driven domain modelling by evaluating different LLMs and various prompt engineering techniques.	P2	S1.a.m, S1.b.m	T3	L3
(Adhikari et al., 2024)	This paper introduces SimIMA, an intelligent modelling assistant for Simulink. It uses association rule mining and model clone detection to support the modeller in developing models.	P3	S1.b.m	T2.b	L1
(Yoo et al., 2022)	This study suggests DDA, an approach to domain-knowledge-integrated, designable data augmentation with transfer learning, which improves the efficiency of deep learning-based metamodelling for complex systems design, such as bumper design for vehicle crash safety.	P2	S1.b.m	T2.c	L1
(Saini et al., 2022)	This paper proposes an approach to bot-modeller interaction. It combines an incremental learning strategy with the discovery of alternative configurations, improving the accuracy of the bot's suggestions through the analysis of domain modelling decisions over time.	P2, P3	S1.b.m	T2.b	L1
(Khalilipour et al., 2022)	This paper classifies Ecore metamodels by using their structural and textual information to improve automated model classification for model management.	P1	S1.b.m	T2.a	L0
(Hartmann et al., 2017)	This study examines an approach to improving domain modelling by incorporating micro-learning into the modelling process.	P3	S1.b.m	T2.a	L0
(Baki and Sahraoui, 2016)	Presents an approach to automatically generate model transformations from examples. The approach is demonstrated through experimental evaluation on seven diverse transformation problems.	P1, P2	S1.b.m	T1, T2.a, T2.b	L3
(Mangaroliya and Patel, 2020)	Explores the automated classification of UML class diagrams into forward-engineered and reverse-engineered diagrams. It provides a dataset with ground truth for the classification of class diagrams.	P1, P3	S1.b.m	T2.b	L2
(Acher and Martinez, 2023)	Presents an experience report detailing the use of LLMs to analyse and transform software variants represented in various formalisms (Java, UML, Graph Markup Language (GraphML), statecharts).	P1, P2	S1.b.m, S1.c.m	T3, T4	L2
(Eramo et al., 2024)	Presents a software architecture for the AI-augmented automation of DevOps pipelines to address both architectural and technical challenges associated with the development and operation of complex systems.	P1	S1.b.m, S1.e.m	T2.c	L2
(Babur, 2016)	Proposes an approach for statistically analysing large collections of models within the field of MDSE. The approach demonstrates its effectiveness in domain analysis and repository management, and shows the potential for applications such as model clone detection.	P1	S1.b.m, S1.e.m	T2.a, T2.b	L1
(Xue, 2023)	This work proposes Code Generation By Example (CGBE), a code generation approach that has been learned from examples for UML to Java code generation.	P2	S1.c.m	T1	L1
(Lin et al., 2024)	Introduces FlowGen, a code generation framework that leverages multiple LLM agents to emulate different software process models (Waterfall, Test-Driven development (TDD), and Scrum). On standard benchmarks, the Scrum-based FlowGenScrum consistently outperforms other models and baselines.	P2	S1.c.m, S1.d.m, S1.e.m, S3.1.m, S3.2.m	T3, T4	L3
(Tamizharasi and Ezhumalai, 2024)	This study presents an approach to deriving feature models in UML from historical source code, which can then be used as a basis for generating and prioritising test cases.	P2	S1.d.m	T2.b	L2

Table 2: AI-augmented model-driven software engineering (sorted by application targets)

approach for the gradual, goal-driven refinement of incomplete domain models provided by human experts. The system learns general rules from specific examples and

refines or extends concepts in order to handle exceptions caused by model incompleteness. An intelligent modelling assistant for Simulink is presented in (Adhikari et al., 2024). It offers two forms of data-driven guidance: SimGESTION provides real-time edit suggestions using ensemble learning, while SimXAMPLE recommends related models through clone detection.

Model management is central to MDSE and is therefore an active area of research. The methodology in (Babur, 2016) uses techniques from information retrieval, NLP, and ML to enable the efficient comparison, clustering and clone detection of model artefacts. The automated classification of UML class diagrams into forward-engineered and reverse-engineered diagrams presented in (Mangaroliya and Patel, 2020) provides another perspective on model management that is crucial for understanding the evolution of software projects. Different to that, (Khalilipour et al., 2022) focuses on Ecore metamodels and presents results showing that incorporating structural information significantly improves the accuracy with which models are classified, which in turn helps to improve the comparison, clustering, and clone detection of model artefacts.

Model transformation has also been studied: (Baki and Sahraoui, 2016) presents a novel method for automatically generating model transformations from examples. It employs a three-step process: (1) analysing example model pairs to identify groups of similar transformations, (2) using genetic programming to learn basic rules for each group, and (3) refining these rules using simulated annealing to handle complex dependencies and value derivations. The method presented improves the efficiency and accuracy of learning complex model transformations.

Code generation supported by models and AI has also been a key research field: (Xue, 2023) aims to improve the synthesis of reusable and adaptable code generators in MDSE by reducing the manual effort typically required. The proposed approach, Code Generation By Example (CGBE), uses symbolic machine learning and tree-to-tree mappings to learn code generation from UML to Java. (Lin et al., 2024) uses agentic AI where each agent embodies a specific development role such as requirement engineer, developer, or tester and collaborates via chain-of-thought prompting. The set of LLM agents emulate different software process models and are evaluated against four benchmarks. The impact of individual development activities on code quality is also investigated, revealing the critical role of testing and the beneficial effects of design and code review

Similarly, testing is an important area for applying improved generation methods from models supported by AI. The test case generation and prioritisation presented in (Tamizharasi and Ezhumalai, 2024) addresses the challenges of resource constraints, high costs and inefficiencies in traditional test development methods.

Case studies on AI-augmented MDSE have also been published. (Acher and Martinez, 2023) explores the use of LLMs to aid in the complex process of re-engineering existing software variants into a software product line (SPL) by identifying features to represent variability and commonalities. It describes the methodology used to prompt the LLMs, the results obtained, and the limitations encountered. There is a potential in assisting domain analysts and developers in transforming software variants into SPLs, but LLMs are limited in managing large variants or complex structures. (Eramo et al., 2024) presents a novel software architecture designed to address the increasing

complexity of modern system development within a DevOps framework. The architecture integrates MDSE and AI techniques to enhance the entire software lifecycle, from requirements engineering to monitoring and maintenance. The architecture is evaluated through multiple industrial case studies.

All papers share the common view that the strengths of AI and MDSE should be combined to further improve the quality of software products and/or processes. While acknowledging the potential of AI-supported MDSE, the papers also highlight the limitations of LLMs, their sensitivity to prompt variations, their limited ability to handle complex inputs, and the risk of inaccuracies. There is a consensus that a fully automated approach is not yet feasible and that human review remains necessary to counteract inaccuracies introduced by AI. UML is seen in these papers as a common modelling language, both for creating models and as an input to AI models. There is also an expectation that AI techniques will support better model quality and improve software reuse by identifying and adapting components from previous projects. This will be supported by the use of model matching and clone detection techniques.

In general, the potential of using AI for MDSE can be summarised as follows: MDSE provides the formal structure and 'guardrails' that are required for AI to operate effectively and reliably. In turn, AI provides the intelligence and flexibility needed to automate the most challenging and creative stages of the MDSE lifecycle. To realise these prospects in industrial SE practices, the following opportunities require broader uptake:

- (1) The provision of large amounts of **top-down models** on coding platforms.
- (2) The generation of **bottom-up models** from big code.
- (3) The formation of **Big Models** as a basis for more advanced empirical MDSE and further improvements of MDSE.
- (4) The **application of AI methods** on big models and for big models.
- (5) The shift towards the paradigm of **pair modelling** in industrial SE practice will altogether turn SE into the **next generation of software engineering**.

Regarding **opportunity (1)**, (Störrle et al., 2014) presented the first entities of the SEMI Software Engineering Models Index, a catalogue of model repositories, and invited further contributions to SEMI. (Hebig et al., 2016) used another approach of mining GitHub for projects including UML models, which could well be combined with the SEMI initiative. As a result of numerous efforts towards SE model collections, the Lindholm dataset was developed (Robles et al., 2017) and reviewed in (Robles et al., 2023). For recent work on ground truth datasets see Table 2.

In view of **opportunity (2)**, extracting representational models from code is in fact the opposite of using models to generate code more efficiently. Since the design, specification, and maintenance of such models can be complex and time-consuming, various techniques have been developed to extract models from code and/or execution traces. These techniques include the extraction of all types of models including for example the extraction of information models, see e.g. (Burson et al., 1990; Murphy and Notkin, 1996), of structural models, see e.g. (Kazman et al., 1998; Guo et al., 1999), and of behavioural models, see e.g. (Corbett et al., 2000; Lo et al., 2009). The process of extracting models from code and/or execution traces offers the advantage

of retrieving models that are up-to-date with the code/traces, but it also carries the potential disadvantage of mismatch with the model representation and abstraction requirements.

With regard to **opportunity (3)**, there are initial studies on big models such as ([Ho-Quang et al., 2017](#)) which explores the increasing role of modelling, especially in safety-critical software development. It surveyed a range of projects utilising the UML and identified collaboration as the primary rationale for employing models. This is because models facilitate communication and planning for joint implementation efforts within teams, including those who are not directly involved in modelling or are new to the team.

For **opportunity (4)**, Table 2 elaborates the current state of research in more detail.

Finally, regarding **opportunity (5)**, the pair modelling paradigm was initially proposed in ([Kamthan, 2008](#)) when a great deal of work was being conducted on top-down MDSE. In the era of AI-augmented software engineering (SE), the pair modelling paradigm has evolved once again as a natural progression from the pair programming paradigm ([Bipp et al., 2008](#)), which has developed into one of AI's killer applications in SE. Based on big models and "foundation/large models for MDSE" (in analogy to LLM, i.e. large models for ML trained on SE models), AI-supported pair modelling may also become a central AI application for MDSE: AI-powered tools and agents could act as pair modellers and partners in software development. See, for example, ([Dakhel et al., 2023](#)) for similarities with pair programming. The engineer or tool/agent in the role of the driver writes or improves software artefacts, including models, while the other, in the role of the observer, reviews each element of the software artefact as it is typed into an artefact. The one in the role of observer is also in the role of navigator, considering systemic and strategic aspects of software development: The navigator identifies potential improvements and possible upcoming problems that need to be addressed later on if they are not to be avoided. This allows the driver to focus on the development aspects without losing sight of the cross-cutting and overarching aspects of software development. As with pair programming, pair modelling uses an observer to ensure the quality of the final software and guide high-quality software engineering. The driver and observer/navigator can switch roles. Indeed, the exact interplay of driver and observer/navigator in pair modelling depends on the capabilities of the AI tool and the level of automation support, it can provide to the software engineer being in either role.

## 6 Related Work

As this paper's main contribution is the *ai4se* taxonomy, which was developed through a literature review of AI for SE (including MDSE), the related work section reviews literature survey approaches and taxonomy developments in the emerging field of AI applications in SE. Classifying research papers within this taxonomy also led to a discussion of opportunities in AI for MDSE. Therefore, the related work section also covers roadmaps on this topic.

Systematic literature reviews are used to explore the status of a research field by examining the results of published research presented in peer-reviewed papers that are available online. Numerous SLRs on AI for SE have been published. While some categorise the reviewed research, none have developed a taxonomy for classifying the field of AI for SE. Table 3 presents a selection of recent SLRs on AI for SE.

Paper	Summary	Difference to <i>ai4se</i> SLR
(Alenezi and Akour, 2025)	This paper focuses on the benefits of AI for SE, such as increased productivity, improved code quality and faster development, and on key impact areas such as automated coding, intelligent debugging and predictive maintenance. The paper supports its findings with case studies and theoretical models from various activities in SE.	SLR with focus on case studies.
(Durrani et al., 2025)	This study provides a quantitative assessment of the impact of AI in SE phases. It suggests that AI can improve the accuracy of planning and requirement engineering, as well as enhancing the efficiency of the latter and the software design.	
(Hou et al., 2024)	This study analyses LLMs for SE by characterising their features, reviewing data curation and training processes, and evaluating their performance and success in application to SE.	SLR on LLMs for SE.
(Mohammad and Chirchir, 2024)	This study examines the main challenges of applying AI to project management, particularly during the planning stage.	SLR on AI for project planning.
(Zhang et al., 2024)	This paper provides an overview of the general workflow of learning-based automated program repair techniques. It outlines related empirical studies and provides evaluation metrics.	SLR on AI for program repair.
(Durrani et al., 2024)	This paper aims at identifying the AI techniques most often used in software development and their effects on the accuracy and efficiency of software development activities.	SLR on software development.
(Wang et al., 2024)	This paper investigates the software testing tasks for which LLMs are typically employed, the most prevalent LLMs, the types of prompt engineering employed alongside these LLMs, and the associated techniques.	SLR on LLMs for testing.
(Kumar et al., 2023)	This study analysis the advances of AI for SE, the potentials for future development as well as the risks of AI application to SE.	SLR combined with qualitative expert interviews.
(Wong et al., 2023)	This paper provides a review of transformer-based LLMs that have been trained using big code and are used for NLP techniques in AI-assisted programming.	SLR on NLP utilization for programming.
(Wang et al., 2023)	This study examines the complexities involved in applying ML/DL solutions to SE. It also explores how these issues affect the reproducibility and replicability of ML/DL applications in SE.	SLR on ML/DL for SE.
(Mohammadk et al., 2023)	This study explores the extent to which explainable AI has been investigated within the SE community. Software maintenance, and defect prediction in particular, is the area of SE that has received the most attention in terms of the stages and tasks being studied.	SLR on explainable AI for SE.
(Fan et al., 2023)	This paper reviews the use of LLMs in SE and highlights the important role of a hybrid approach combining traditional SE and LLMs in achieving reliable, efficient and effective LLM-based SE.	SLR on LLMs for SE.

**Table 3:** SLRs on AI for SE (sorted by publication year)

Another important area of research is the development of roadmaps. Like SLRs, these seek to evaluate and categorise developments thus far. In addition, however, they

project these developments into the future. The roadmaps presented in Table 4 were recently published.

Paper (Terragni et al., 2025)	Summary	Difference to <i>ai4se</i> taxonomy
(Abrahão et al., 2025)	This study examines how AI is reshaping the role of humans within the software ecosystem. It explores the challenges and opportunities arising from the interaction between technical and human factors in human-centred workflows.	This categorization of AI for SE focuses on how AI can enhance SE, render technologies and approaches obsolete, overturn common practice, retrieve past results, and change workflows. Human factors have yet to be incorporated into <i>ai4se</i> , and could be considered a new dimension.
(Ahmed et al., 2025)	This study highlights three key challenges for AI in SE: the use of GenAI and LLMs for engineering large software systems; the requirement for large, unbiased datasets and benchmarks for training and evaluating DL and LLMs for SE; and the need for a new code of digital ethics for applying AI in SE.	By analysing the challenges in classical and upcoming SE processes, the relevance of human factors in SE is also emphasised (see also (Abrahão et al., 2025)).
(Di Rocco et al., 2025)	This paper presents an overview of current LLM applications in MD[S]E and a roadmap for the deployment of LLMs to enhance the management, exploration, and evolution of modelling ecosystems.	The status of LLMs for MDSE is presented as a feature model. In particular, the more detailed modelling tasks could be considered new facets of MDSE in <i>ai4se</i> .
(Marchezan et al., 2024)	This paper explores the potential applications of GenAI in model-driven software maintenance and evolution.	As represented in <i>ai4se</i> , this paper explores how MDSE can be advanced through AI, particularly GenAI. It emphasises that AI can assist modellers, enhance their capabilities, and facilitate reasoning and automation in MDSE.
(Bannon, 2024)	This study analyses the infusion of AI techniques into DevOps and software security-related tasks. It also presents a call for action towards GenAI-based agents for SE.	The study emphasises the importance of human factors, security and trust considerations, all of which are candidate extensions for <i>ai4se</i> .
(Lo, 2023)	This paper reviews the development stages of AI for SE, highlighting trust and synergy as two key challenges that must be overcome before AI for SE tools can act as intelligent, responsible workmates.	The paper proposes research into trust-aware, privacy-aware, licence-aware, attack-resistant, secure and workflow-aware AI for SE solutions. This could potentially lead to new research being classified in the <i>ai4se</i> taxonomy.
(Nguyen-Duc et al., 2023)	With the help of an SLR, this paper identifies 78 open research questions across 11 SE areas for a GenAI-based SE solution. A research agenda is derived that highlights the need for solutions in the areas of dependability and accuracy, data accessibility and transparency, and sustainability aspects of GenAI solutions for AI.	These requirements could potentially lead to new research being classified in the <i>ai4se</i> taxonomy. Moreover, the 'quality' aspects of AI for SE solutions, such as accuracy, robustness, transparency and sustainability, have the potential to be an extension of <i>ai4se</i> .

**Table 4:** Research roadmaps on AI for SE (sorted by publication year)

Last but not least, some papers have investigated the development of a taxonomy for AI for SE, often focusing on a subfield of SE or the AI techniques used, as described in Table 5.

Paper	Summary	Difference to <i>ai4se</i> taxonomy
(Treude and Gerosa, 2025)	The types of interaction between software developers and AI are the focus of this taxonomy.	Human factors are a candidate extension for <i>ai4se</i> .
(Melegati and Guerra, 2024)	The DAnTE taxonomy focusses on the degree of automation of SE tools in general and defines six levels, including no automation, informer, suggester, and local, global and full generators. It also reviews AI for SE in particular.	DAnTE considers three types of generator, whereas <i>ai4se</i> differentiates between partial and full generators only. The differences between 'global' and 'full' are subtle, and no tool currently addresses these levels.
(Zhao et al., 2022)	This taxonomy organizes 57 most frequently used NLP techniques in requirements engineering (RE).	This NLP classification could be used to further refine the AI types in <i>ai4se</i> .
(Sofian et al., 2022)	This systematic mapping study examines the use of four types of AI (and their combinations) in the development, deployment and maintenance of software.	While the AI types and the SE activities in <i>ai4se</i> are more detailed, this mapping's approach is similar. Still, for <i>ai4se</i> , it could be considered to make the (AI) training a separate activity.
(López-Luján et al., 2021)	This systematic mapping study examines the use of AI in component-based SE and its potential to support this field. Not only does it map AI approaches to SE activities, it also identifies the problems being addressed.	<i>ai4se</i> considers SE in general rather than component-based SE specifically. Nevertheless, some of the AI types and targets, which are the 'problems' in this study, may be considered for inclusion.
(Erlenhov et al., 2019)	This study focuses on bots that support software development (DevBots). It classifies contemporary DevBots using a facet-based taxonomy and outlines the ideal characteristics of future DevBots. The main facets are purpose, initiation, communication and intelligence.	While the main facets 'purpose' and 'intelligence' essentially correspond to the <i>ai4se</i> dimensions 'purpose' and 'AI type', 'initiation' and 'communication' could be considered for inclusion in <i>ai4se</i> as part of the human factors.
(Feldt et al., 2018)	This study introduces the AI-SEAL taxonomy, which classifies AI solutions for SE based on their application point, the type of AI technology employed, and the degree of automation they offer.	AI-SEAL uses three high-level SE processes, five AI tribes for categorising AI types and ten automation levels to determine the level of automation support. In contrast, <i>ai4se</i> provides a detailed view of SE, categorising AI types into seven categories and automation levels into five.

**Table 5:** Taxonomies on AI for SE (sorted by publication year)

The SLRs, roadmaps, and taxonomies presented in Tables 3, 4, and 5 show that the intersection between AI and SE is a rapidly growing area of research and tool development. AI support in SE is used to address areas such as code generation, defect detection, code repair, code documentation, software testing, and challenges relating to software quality, security, and piracy. The application of AI in MDSE to rail guard the application of AI by models is another focus.

Only a few taxonomies for SE and AI have been made explicit so far. They address a specific subfield of SE only or focus on classifying the AI methods and techniques used. Still, all of these taxonomies essentially align with *ai4se*. In addition, the taxonomies in (Feldt et al., 2018; Melegati and Guerra, 2024) and (Erlenhov et al., 2019) highlight the need to detail human factors when analysing the potentials of AI for SE. In future work, *ai4se* is to be extended accordingly.

## 7 Summary and Outlook

Following a review of the current state of model-driven software engineering practice, this paper examines big code on open-source software platforms and the application of AI in software engineering. The novel *ai4se* taxonomy is developed and employed

to categorise recent and highly cited publications. This taxonomy aims to classify and understand the various ways in which AI is employed in software engineering, acknowledging the increasing overlap between the two fields. Furthermore, the concept of big models is defined and explored to identify opportunities for further adoption of model-driven software engineering that capitalises on AI progress. Finally, selected research on AI approaches for MDSE is reviewed and categorised using the *ai4se* taxonomy. Future work will focus on contributing to the development of big models and AI applications in MDSE, as well as detailing other SE activities within the taxonomy.

With regard to the research questions provided for the SLR, which formed the basis for the development of the *ai4se* taxonomy, the answers are as follows: The SLR revealed current research on AI for SE and for MDSE as shown in Table 1 and Table 2. Software development and model-driven software design are the primary focus of AI support in SE, but also other SE and MDSE activities are being studied. The *ai4se* taxonomy can classify the identified unique research, that address all dimensions and their facets, but not general purpose AI (T5) or AI-driven full automation (L4). Subsymbolic AI (T2) and generative AI (T3) are often used, agentic AI (T4) is on a rise. The automation levels reached are most often AI-assisted option (L1) and AI-assisted selection (L2).

Overall, integrating AI into SE is expected to make the field more accessible to a more diverse range of users. Increasing the automation of SE tasks frees up developers to focus on higher-level design and problem solving, thereby making the development process more enjoyable and creative. Furthermore, AI-augmented MDSE is regarded as the way forward, seamlessly bridging the gap between higher-level models and concrete code. Large models will facilitate the model-based training of GenAI and Agentic AI across the entire MDSE landscape.

However, it is also crucial to acknowledge the necessity of addressing the ethical implications of AI in SE, particularly with regard to bias, fairness, transparency and privacy, when developing and deploying AI-augmented software tools. Using pair programming and pair modelling with AI has been identified as a way to enhance collaboration between humans and AI, and to address ethical considerations.

Moreover, in order to allow for greater integration of AI into tools, a number of challenges must be overcome. These include establishing interoperability between tools, creating standards and providing user-friendly coding and modelling tools. In the future, AI-augmented software lifecycle frameworks will

1. automate repetitive and often time-consuming tasks,
2. provide intelligent decision-making by analysing big code and big models for deeper insights,
3. enhance the quality of software products by detecting inconsistencies in requirements, design flaws and software defects early in the development lifecycle,
4. facilitate management of the increasing complexity of modern systems by providing analysis, monitoring and optimisation tools, and
5. enable continuous improvement through feedback loops and adaptive learning, fostering iterative improvement in software products and processes.

In order for the community to follow the further evolution of AI for SE and MDSE, the ontology and paper classification along the *ai4se* taxonomy have been made available to the public under a CC-BY-SA licence for use and extension as required.

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