From Task Execution to Task Stewardship: AI-Induced Transformation of Task Profiles in Architecture and Engineering and Its Consequences for Higher Education

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Abstract

Artificial intelligence (AI) is changing the knowledge professions faster than education can respond. In architecture, engineering and construction (AEC), planning is organised into defined service phases, which creates a tension between an agile, iterative use of AI and the rigid, task-bound structure of the classical phase model. This paper asks how AI changes the task profiles of planners and, above all, what competences future engineers and architects therefore need. The contribution is a competence framework for AEC higher education, derived from a systematic literature review and substantiated by a nationwide survey of 1,020 students. The review indicates that AI first takes over routine, document-intensive sub-tasks and shifts the human contribution towards oversight, integration and accountability, a role termed task stewardship, with value concentrating in the early design phases. The survey shows that more than 90 percent of students already use AI, while more than half report no structured training, which quantifies a widening competence gap. From these two sources the framework maps shifting tasks onto required future skills and concrete curricular measures for lifelong learning and skills for the future.

Keywords: *artificial intelligence in education, future skills, competence gap, task stewardship, engineering education, curriculum innovation.*

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1. Introduction

Artificial intelligence (AI) is entering professional practice faster than curricula can adapt, and architecture, engineering and construction (AEC) illustrate this tension in a particularly clear way. On the one hand, generative AI is inherently agile and iterative. On the other hand, planning in the German-speaking context is organised by a rigid, task-bound structure, the classical phase model of the fee schedule for architects and engineers, which divides a project into nine service phases (LP 1 to LP 9) [1]. This paper uses that model only as an analytical reference frame, that is, as a fixed grid against which the AI-induced redistribution of work can be measured, and not as an object of normative critique. The tension between an agile technology and a rigid phase structure is the starting point of the study.

The exposure of AEC to AI is high but strongly discipline-dependent, and construction-specific AI is still at an early stage. Cross-occupational estimates place engineering and architecture among the clusters with the highest technical AI exposure, on the order of 85 percent of tasks, where exposure denotes the potential for AI support and not realised automation [2]. At the same time, dedicated work on AI in construction is only now emerging, for example along the value chain of the sector, across the life cycle of a building and in dedicated engineering-focused proceedings [3][4][5][6], and adoption studies report that only about a quarter to a third of AEC professionals use AI operationally, while trust and maturity remain the main barriers to realised use [7][8]. This gap between potential and practice is compounded on the workforce side, because although a majority of organisations have embedded AI in core processes, only about a quarter of leaders consider their workforce fully prepared [9].

The same gap is visible in higher education, and it is here that the study is focused. A nationwide survey of students in engineering and construction-related disciplines shows that more than 90 percent already use AI chatbots such as ChatGPT in their studies, whereas more than half state that their programme does not train them in a structured way, meaning that AI competences are acquired informally rather than taught [10]. In other words, the way planning work is carried out in practice is beginning to change, the students have already adopted the tools, but the curriculum has not yet responded.

This creates a research need that the established frameworks do not yet cover, and that can be stated in three points. First, the competence side is unclear, because it is not defined which AI-related competences future planners actually require. Second, the task side is unquantified, because the shift of tasks across the service phases has not been measured [11]. Third, the evidence base is thin, because robust, discipline-specific studies on the effect of AI on planning tasks are largely absent. The contribution of this paper addresses the first point directly. For educators and programme designers in AEC higher education, it provides a competence framework that connects the changing task profiles of the profession to concrete curricular measures, and it grounds this framework in both a literature review and primary survey data.

From this need, the study pursues three research questions. (RQ1) Which AI technologies are used in which service phases, and which task profiles are affected? (RQ2) How is the shift of human work best conceptualised? (RQ3) Which competences must AEC higher education convey so that graduates are prepared for these changed task profiles? The remainder of the paper

presents the theoretical background, the methodology, the synthesis of results, the competence framework and a discussion of its implications for teaching.

2. Theoretical background and related work

2.1 Artificial intelligence in construction planning: state of the art

We first summarise the concrete state of the art in the sector before turning to the underlying theory. Four recent reviews can be read as four statements. First, generative AI has become a central driver of innovation in AEC, but its real adoption is still slow and often rudimentary [12]. Second, the highest AI intensity lies in planning and in monitoring and control, yet a quantification of the resulting competence and role shifts is missing [13]. Third, the role and competence side calls for a systematic upskilling of AEC professionals [14]. Fourth, standardised methods for evaluating AI output are still absent [15]. As these reviews are largely open-access surveys, their findings are used here as orientation and are triangulated with the construction-specific literature and the primary survey below.

At the level of specific tools, the evidence is moving from the laboratory into practice, and construction-specific accounts are now available. In proof-of-concept studies, large language model agents carry out structural engineering workflows, including calculation, code-compliance checking and finite-element analysis, so that human work concentrates on specification and validation [16]. Multi-agent frameworks produce code-compliant reinforced-concrete designs without manual iteration [17], and generative AI is used for tasks as specific as construction cost estimation [18]. Recent construction-focused work describes the same movement along the planning phases and the value chain, and it explicitly names the shift of design value into the early phases through front-loading and generative design [4]. These tools affect the design and documentation phases (LP 2 to LP 6) most strongly, and industry evaluations report time savings of around 40 percent in the early phases together with about 30 percent fewer design revisions, figures that are vendor benchmarks rather than peer-reviewed evidence [19]. Figure 1 illustrates the two central dynamics as two panels. Panel (a) shows the role shift that gives the paper its title. Where a planner once spent most of the working time on routine execution, namely the drafting of variants and drawings, standard calculations and standard documents, AI increasingly takes over this execution. The human contribution does not disappear but shifts to, and grows in, task stewardship, that is the framing, oversight, verification and accountability for the AI-supported work. The more the machine executes, the larger the stewardship part of the remaining human work becomes. Panel (b) shows a second and independent dynamic. The leverage of design decisions is greatest in the early phases and declines afterwards, which is what we call front-loading. Across the phases, the automatable execution itself is concentrated in the standardisable design and documentation phases (LP 2 to LP 6) and is lowest in the human-centred phases of needs assessment (LP 1) and of site supervision and handover (LP 8 and LP 9), where both the work and the responsibility stay with the human.

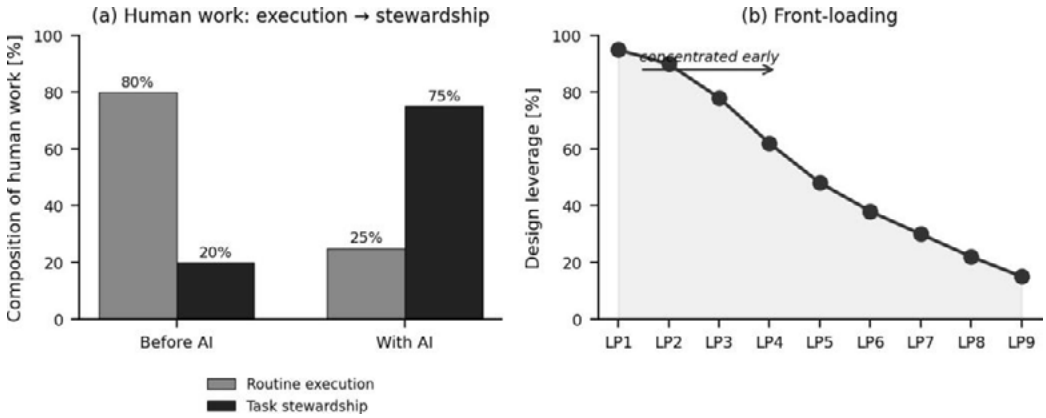


Figure 1. (a) Composition of the planner's work before and with AI support: routine execution (drafting, calculation, standard documents) gives way to task stewardship (framing, oversight, verification, accountability), which grows as AI takes over more of the execution. The legal responsibility for the result stays with the human throughout. (b) Design leverage of decisions across the service phases (front-loading). Schematic, authors' own representation based on the reviewed literature.

2.2 The task-based view of technological change

To interpret this pattern, we draw on the task-based view of technological change, which treats an occupation not as a single unit but as a bundle of separable tasks. In this view, technology does not replace whole jobs but individual tasks, and it does so selectively, substituting for routine, codifiable tasks and complementing the non-routine, analytical and interpersonal ones [20]. Later work extended this logic to AI, describing a race between the displacement of existing tasks and the creation of new ones [21], and made widely known the resulting shift of value towards complementary human skills [22].

Recent empirical analyses specify how this shift plays out. AI-induced polarisation concentrates in skill-adjacent occupations, and tacit, experience-based knowledge correlates positively with wages [23]. A comparative review of exposure measures and ex-post evidence finds sizeable but context-dependent productivity gains and only a limited net displacement of employment [24]. From this a conclusion for engineering follows. Because engineering work combines codifiable calculation with a large share of non-routine coordination, judgement and responsibility, it is the codifiable share that AI substitutes first, whereas the non-routine share is complemented rather than replaced. This is why engineering occupations appear comparatively robust against full substitution, and why the effect is best read as a transformation of tasks rather than a loss of jobs. Two institutional analyses quantify the same mechanism, finding that a majority of work hours are technically automatable while more than 70 percent of today's skills remain applicable in both automatable and non-automatable activities, so that whole workflows rather than isolated tasks should be redesigned [25], and that new activities emerge in the AI age [26].

2.3 Task stewardship as the human role

The upgraded human role that remains after this substitution is what we term task stewardship. A specific term is warranted because the established labels are too narrow for a regulated planning profession. Oversight and supervisory control, taken from control theory, describe monitoring a system but say nothing about who answers for the result. Orchestration denotes the coordination of tools, and augmentation denotes a benefit to the worker. Stewardship, by contrast, is a normative relation, because a steward acts on behalf of others and remains accountable for outcomes. In AEC this is not a metaphor but a legal fact, since the signing planner carries the professional liability for a design regardless of how much of it a machine produced [1]. The same re-weighting of human work towards judgement and responsibility in an AI-shaped construction workplace is described in the recent sector literature [4]. The role that AI leaves to the human is therefore defined less by supervising the tool than by answering for its result, and it is this combination of delegated execution and retained liability that the framework in Section 4 operationalises as competences.

3. Methodology

The study combines a systematic literature review with a complementary student survey, so that the demand side of the profession and the supply side of education are covered from two independent sources.

3.1 Systematic literature review

The review follows the PRISMA 2020 standard and a protocol fixed before data collection (Protocol V1.0, May 2026). Six scholarly databases are searched, namely Scopus, Web of Science, IEEE Xplore, the ASCE Library, ScienceDirect and Google Scholar. Four search strings built on the population-intervention-comparison-outcome scheme combine AI terms with AEC terms and with terms for task transformation, competence and remuneration, and a separate string covers the underlying theory. The core time frame is 2018 to 2026, extended to 2003 to 2026 for the theoretical literature. Inclusion and exclusion criteria follow the SPIDER framework and admit studies that address AI in planning processes and report measurable statements on time, cost, quality, role shift or competence. Screening runs through the four PRISMA phases of duplicate removal, title and abstract screening, full-text assessment and quality appraisal, with a ten-percent inter-rater subsample (target Cohen's kappa of at least 0.70), CASP and NIH quality appraisal, and a narrative synthesis. Figure 2 shows the corresponding PRISMA flow with the planned yield at each stage and the exclusion reasons. The synthesis presented below rests on the studies already extracted, and the final counts will replace the planned figures once screening is closed.

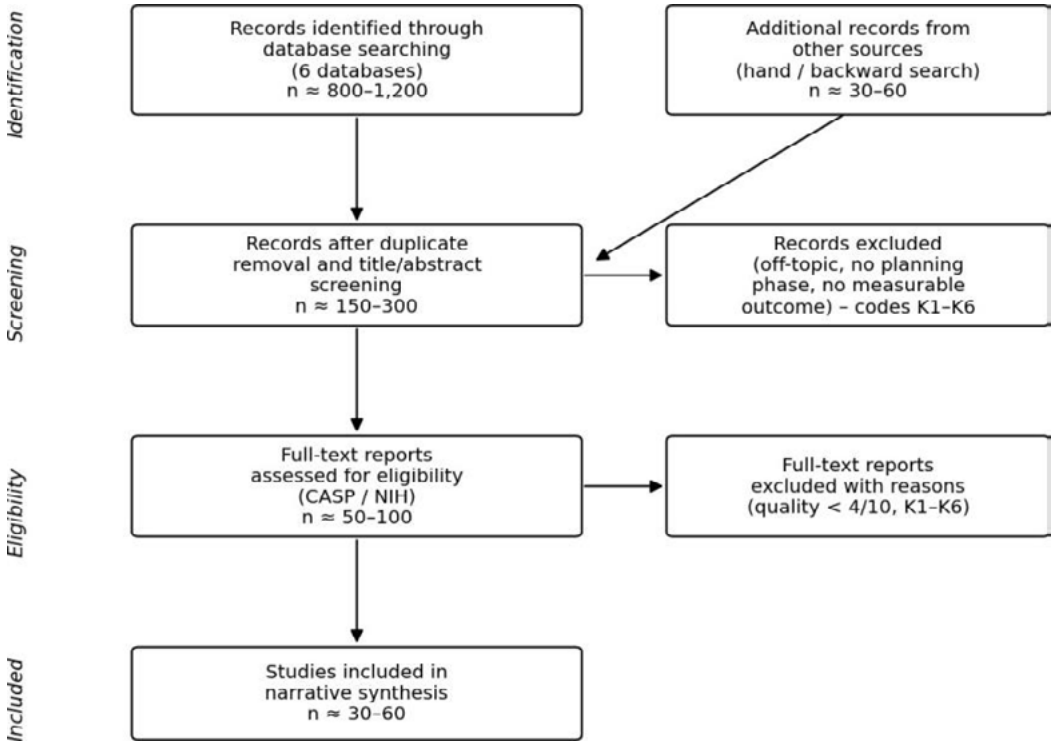


Figure 2. PRISMA 2020 flow of the literature review with exclusion reasons (planned figures per Protocol V1.0, final counts to follow).

3.2 Complementary survey (KI4Edu)

The educational side draws on the KI4Edu survey, a descriptive online study distributed across German higher education institutions between July and October 2024 and funded by the Foundation for Innovation in Higher Education. The questionnaire of 39 items was disseminated online through university channels and analysed descriptively. Of 1,123 responses, 1,020 valid cases from students at 85 institutions remained after data cleaning. The sample is 52 percent male and 47 percent female with a mean age of 23.9 years, and engineering and construction-related disciplines are deliberately over-represented in line with the research focus [10]. The survey provides the primary evidence for the competence gap and the empirical anchor for the framework in Section 4.

4. Results: a competence framework for AEC higher education

The central result of the study is the competence framework in Table 1. It is built in two steps. The literature review identifies, for each cluster of service phases, which tasks AI takes over and which human role is upgraded, and the student survey then supplies the empirical evidence that these competences are in demand but not yet taught. Table 1 therefore reads the shifting task profile of the profession directly into the future skills and the curricular measures that AEC programmes require.

4.1 From shifting tasks to required competences (RQ1, RQ2)

Across the reviewed studies, AI is not distributed evenly over the phase model. It concentrates on the standardisable, computation- and document-heavy sub-services of the early and middle phases, namely variant generation and optimisation in LP 2 and LP 3, code-compliance checking in LP 3 and LP 4, execution drawings in LP 5, and the drafting of bills of quantities and tender documents in LP 6. The integrative, negotiation- and responsibility-intensive activities of the later phases are least affected. The contribution of the synthesis is not the observation that these tools exist, but the reading of their uneven distribution as a single pattern. AI takes the codifiable sub-tasks, while the framing of the task, the integration of disciplines and the responsibility for the result stay with the human. It is this pattern that we conceptualise as task stewardship, and it is this residual human role, and not the tool, that defines the competences an education must convey.

4.2 Evidence from the student survey (RQ3)

The survey validates the demand for these competences and quantifies the gap. More than 90 percent of the surveyed students use AI, 85 percent use chatbot assistants such as ChatGPT, and 20 percent use them daily. At the same time, more than half report no structured training, and a majority use the tools mainly for explanation and research rather than for professional judgement [10]. Figures 3 and 4 summarise these results, including the purposes and the frequency of AI use. The pattern is consistent with the reviewed risk that uncritical reliance on generative tools can lower the cognitive effort that users invest, which makes the deliberate training of critical judgement a central objective rather than an optional one [27]. Read together, the review and the survey show a demand for stewardship competences on the profession side and an untrained supply on the student side, which is exactly the gap that Table 1 is designed to close.

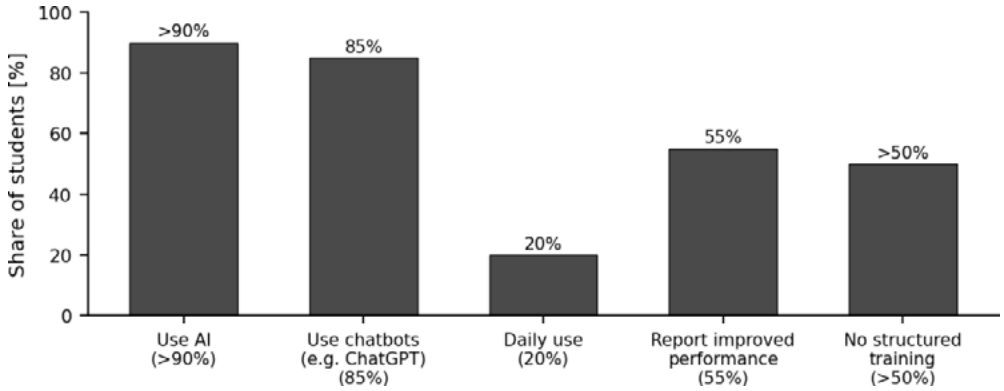


Figure 3. Selected results of the KI4Edu student survey (N = 1,020, 85 institutions), authors' own representation.

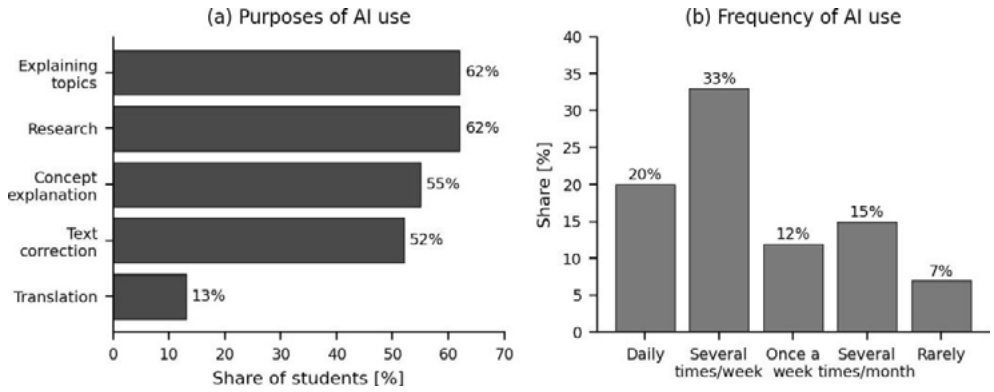


Figure 4. Purposes and frequency of AI use among the surveyed students (KI4Edu, N = 1,020), authors' own representation.

Shift in the task profile	Required future skill (stewardship)	Curricular measure
From manual variant production to steering generative tools	Prompting, specification and critical evaluation of AI output	Project- and studiobased modules with AI in the loop and mandatory verification
From norm checking to validating automated compliance	Norm literacy and verification of machinegenerated results	Assessment redesigned around judgement rather than reproduction
From isolated tools to integrated workflows	Data governance, liability awareness and AI ethics	Crossdisciplinary, challengebased modules on data, ethics and liability
From information retrieval to critical reasoning	Critical thinking and source appraisal under AI use	Explicit training of critical judgement across the curriculum
From content delivery to mentored learning	Selfdirected, reflective use of AI as a learning partner	Educator as mentor and quality assurer in AIsupported teaching

Table 1. Competence framework: shifting task profile, required future skill and curricular measure for AEC higher education.

5. Discussion: implications for teaching

The framework has concrete consequences for how AEC programmes teach. To say that curricula should follow the profession means, specifically, three things. First, the stewardship competences of specification, prompting, verification and accountability should be taught as core content, because these are the activities that remain with the human when routine subtasks are automated, a division that the reviewed literature supports and that the survey shows students do not yet learn [14]. Second, these competences are future skills that are best acquired by doing, which points to challenge-based and project-based formats in which students steer AI tools on realistic tasks and must verify the output, rather than to added lectures, and which also require ways to assess such competences [28][29]. Sector-specific proceedings likewise stress these new skills for engineering practice [6]. Third, because uncritical use lowers cognitive effort, the explicit training of critical judgement should run across the curriculum [27].

The teaching role changes as well, although this should be read as a proposal rather than a claim. In AI-supported teaching the educator can move from delivering content towards mentoring, quality assurance and the curation of verified material, while the tool widens access to knowledge. A prototype of this division of labour has been implemented and tested in a retrieval-augmented tutoring system [30]. Whether this re-weighting of the teaching role is desirable and effective is an open question that the authors do not claim to settle here, and it should be examined empirically before it is generalised.

Several limitations qualify these results, and naming them is part of the evaluation. What is already available is the extracted body of literature and the completed KI4Edu survey, and the framework rests on these. What is still in progress is the final full-text screening of the

review, so the synthesis should be read as a well-founded preliminary result that the authors are continuing to consolidate. The survey, moreover, is a single-country, self-report study that over-represents engineering students, which limits generalisation. Its data were collected in 2024, which is recent but not trivial given the speed of the field, and the reported usage rates are therefore best read as a lower bound, since adoption has since grown rather than fallen. On this basis the framework is offered as a structured hypothesis for AEC education, to be refined in the further steps described below.

6. Conclusion and future work

AI is transforming the task profiles of planning in the AEC sector by taking over routine, document-intensive sub-tasks and upgrading the human role to task stewardship, with value concentrating in the early phases. The central contribution of this paper is a competence framework that translates this shift into future skills and concrete curricular measures for AEC higher education, grounded in a systematic review and substantiated by a survey of 1,020 students in which more than 90 percent use AI while over half receive no structured training. More generally, the study suggests that preparing graduates for an AI-shaped labour market is less a matter of adding a tool to the syllabus than of reorganising what and how we teach around the competences that remain distinctively human, a question of lifelong learning and future skills that reaches beyond a single discipline.

Several tasks remain before the framework can be considered validated. The literature synthesis must be completed and reported with a full PRISMA account of the screening, the survey results should be analysed in more detail with respect to disciplines and usage patterns, and the framework itself should be tested with educators and students. Methodologically, the authors intend to pursue this through expert interviews and a living-lab measurement of real projects that records the effort of each service phase with and without AI support, and through dedicated student theses that generate further primary data. The framework presented here is the first step of that programme.

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The use of AI tools

The authors used AI-based assistants for language editing, for organising the literature and for translating selected parts of the manuscript. All content was reviewed, verified and approved by the authors, who take full responsibility for the manuscript.