Integrating Artificial Intelligence Competencies in Engineering Education

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Education is the passport to the future,

for tomorrow belongs to those who prepare for it today.

Malcolm X

Abstract

Artificial Intelligence (AI) emerges as a transformative technology across industries. It reshapes how we work and creates new demands for AI competencies and education. This dissertation explores the integration of AI competencies in the context of engineering education, addressing gaps in their conceptualization and operationalization at the program and course level.

The state of the art provides a systems perspective on the integration of AI competencies, including a novel contextualization of AI competencies and an overview of AI education, with a focus on the role of educators. To address the question of *how to conceptualize domain-specific AI competencies in engineering*, the dissertation develops an AI competency profile for engineering. This profile includes professional, methodological, social, and self-competencies, validated through expert interviews and a survey with an expert panel of 32 practitioners from industry and academia. Focusing on *how to develop and evaluate an interdisciplinary AI curriculum*, the dissertation also proposes a structured, participatory process for creating interdisciplinary programs. This development process is evaluated through a case study, including data collection on the process with 14 participants and a self-evaluation of the facilitators. In addition, the outcome of development is validated through structured focus group interviews with 19 participants from education and industry, and curriculum outcome mapping. The findings highlight the importance of stakeholder collaboration, transparency, and scaffolding to ensure curricular integration and coherence. Finally, to address *how a structured framework can support educators in integrating AI competencies into courses*, the dissertation develops a prototype of a course design framework for AI courses using a design-based approach. This framework provides educators with a structural guide to adapt their teaching and effectively integrate AI competencies, empowering them to effectively navigate curricular changes. In total, over 100 educators interacted with the design prototype, while 29 participated in dedicated data collection workshops.

Overall, the dissertation contributes to the emerging field of AI education by focusing on domain-specific AI education in engineering. It advances the theoretical understanding of domain-specific AI competencies and interdisciplinary curriculum design, while providing practical tools to support educators. The findings provide actionable insights for policymakers, curriculum developers, educators, and researchers to design and implement interdisciplinary AI programs. In addition, the developed AI Course Design Planning Framework serves as a practical guide for educators, enabling them to align their teaching with the evolving needs of AI education.

Zusammenfassung

Künstliche Intelligenz (KI) entwickelt sich in allen Branchen zu einer transformativen Technologie. Sie verändert die Art und Weise, wie wir arbeiten, und schafft neue Anforderungen an KI-Kompetenzen und -Ausbildung. Diese Dissertation untersucht die Integration von KI-Kompetenzen im Kontext der Ingenieurausbildung und befasst sich mit Lücken in ihrer Konzeptualisierung und Operationalisierung auf Programm- und Kursebene.

Der Stand der Technik beschreibt die Systemperspektive auf die Integration von KI-Kompetenzen, einschließlich einer neuartigen Kontextualisierung von KI-Kompetenzen und eines Überblicks über die KI-Ausbildung mit Schwerpunkt auf der Rolle der Lehrenden. Um die Frage zu beantworten, wie domänenspezifische KI-Kompetenzen in den Ingenieurwissenschaften konzeptualisiert werden können, entwickelt die Dissertation ein KI-Kompetenzprofil für die Ingenieurwissenschaften. Dieses Profil umfasst Fach-, Methoden-, Sozial- und Selbstkompetenzen, die durch Industrieinterviews und eine quantitative Befragung eines Expertenpanels von 32 Praktikern aus Industrie und Wissenschaft validiert wurden. Die Dissertation konzentriert sich auch auf die Frage, wie ein interdisziplinäres KI-Curriculum entwickelt und evaluiert werden kann, und schlägt einen strukturierten, partizipativen Prozess für die Entwicklung interdisziplinärer Programme vor. Der Entwicklungsprozess wird anhand einer Fallstudie evaluiert, die eine Datenerhebung über den Prozess mit 14 Teilnehmenden und eine Selbstevaluation der moderierenden Personen umfasst. Darüber hinaus werden die Entwicklungsergebnisse durch strukturierte Fokusgruppeninterviews mit 19 Lehrenden und Praktikern aus der Industrie sowie durch einen Curriculum Mapping Prozess validiert. Die Ergebnisse zeigen, wie wichtig die Zusammenarbeit zwischen den Akteuren, Transparenz und aktive Unterstützung des Lernprozesses sind, um die Integration und Kohärenz des Curriculums zu gewährleisten. Um schließlich die Frage zu beantworten, wie ein strukturierter Rahmen Lehrende bei der Integration von KI-Kompetenzen in Lehrveranstaltungen unterstützen kann, stellt die Dissertation einen praktischen Rahmen für die Planung von KI-Kursen vor, der mit einem designbasierten Ansatz entwickelt wurde. Dieser Rahmen bietet Lehrenden einen strukturellen Leitfaden, um KI-Kompetenzen effektiv in ihre Kurse zu integrieren und curriculare Veränderungen zu steuern. Insgesamt interagierten über 100 Lehrende mit dem Design-Prototyp, während 29 an speziellen Workshops zur Datenerhebung teilnahmen.

Zusammenfassend leistet die Dissertation einen Beitrag zum aufstrebenden Feld der KI-Ausbildung, indem sie sich auf die domänenspezifische KI-Ausbildung im Ingenieurwesen konzentriert. Sie fördert das theoretische Verständnis von domänenspezifischen KI-Kompetenzen und interdisziplinärer Curriculumsgestaltung und bietet gleichzeitig praktische Werkzeuge zur Unterstützung von Lehrenden. Die Ergebnisse liefern umsetzbare Erkenntnisse für politische Entscheidungsträger, Curriculumentwickler, Lehrende und Forschende, um interdisziplinäre KI-Programme zu entwerfen und umzusetzen. Darüber hinaus dient das entwickelte KI-Kursplanungsinstrument als praktischer Leitfaden für Lehrende, der es ihnen ermöglicht, ihre Lehre an die sich entwickelnden Bedürfnisse der KI-Ausbildung anzupassen.

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1 Introduction

1.1 Motivation

Artificial Intelligence (AI) has become a transformative force across multiple industries, driven by technological advances, user-friendly interfaces, and widespread accessibility to AI tools [105]. As defined by the Organization for Economic Cooperation and Development (OECD) [243], "an AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment." [243, p. 4].

The integration of AI into user-facing technologies and work practices is changing the way we work and the skills required to do so. Automated meeting summaries, agent interactions, or advanced data analytics are just three examples of how AI impacts work and life [191, 348]. Recent industry reports show an increase in the use and adoption of AI, especially among knowledge workers, as well as a growing demand for AI talent and AI skills in the workforce [215, 266]. Thus, learning about AI is becoming relevant to a broader audience beyond Computer Science (CS) [177], for example in the context of engineering education.

In the educational context, there are two main streams of discussion and research: *using AI in education* and *learning about AI* [31, 343]. The former focuses on integrating AI into teaching and learning processes, such as predicting and profiling learning experiences, providing adaptation and personalization, assessing outcomes, or developing entire intelligent tutoring systems [31]. The latter emphasizes equipping students and society with the competencies to navigate a world increasingly influenced by AI [177, 191, 255]. With a breadth of research targeting the challenges around AI in teaching and learning [31, 66, 343], the dissertation addresses the not well explored area of learning about AI.

Learning about AI In a broader sense, learning about AI describes the acquisition of knowledge, skills, and attitudes about AI systems, such as how AI works, its applications in different domains, and the implications of its use [8, 177, 191]. This is often referred to as AI literacy [8, 177, 191] (discussed further in Section 3.2). Learning about AI is relevant from several perspectives:

From a *legal perspective*, the *European Union (EU) AI Act* places the requirement for AI literacy prominently, stating in Article 4 [263] that “Providers and deployers of AI systems shall take measures to ensure, to their best extent, a sufficient level of AI literacy of their staff and other persons dealing with the operation and use of AI systems on their behalf, taking into account their technical knowledge, experience, education and training and the context the AI systems are to be used in, and considering the persons or groups of persons on whom the AI systems are to be used.” [263, Article 4].

From a *social and ethical perspective*, critical, responsible, and informed use of AI systems is important and highlighted by several studies [8, 153]. Understanding the capabilities and limitations of AI, as well as implications such as bias, privacy, and potential misuse, is essential for informed use and requires learning about AI [124].

In addition, AI systems continue to improve their core capabilities and, as a result, are increasingly displacing jobs. Recent studies have shown that AI systems solved 80% of the literacy and numeracy tests in the OECD Survey of Adult Skills [245], and the International Monetary Fund (IMF) estimates that about 40% of global employment will be exposed to AI [93]. This leads to the *employability perspective*, where AI competencies are in high demand [215, 271] and AI systems start changing roles, work practices, and responsibilities in the respective disciplines [11, 12, 125, 329]. For example, the World Economic Forum’s January 2025 Future of Jobs Report [340] found that 77% of employers plan to reskill and upskill their employees by 2030 to enhance collaboration with AI. Thus, there is a clear need to learn about AI from multiple perspectives.

At the same time, the conceptualization of these capabilities and how to develop them can be approached from multiple directions [204]. The following dissertation addresses learning about AI in the context of higher education, particularly engineering education, but aspects of it may also be applicable to school education (hereafter referred to as the international notion of K-12 education) or vocational education. In particular, it addresses a gap in learning about AI in the context of engineering education and a gap in curriculum change towards AI.

Gap in Learning about AI in Engineering Education Learning about AI also includes a context-specific part, emphasizing that in addition to a general understanding, it is necessary to understand different data, use cases, or implications of a particular domain [153, 254]. In the context of engineering, this might include working on predicting maintenance of machines based on sensor data [182] or using advanced computer vision algorithms for quality control [86].

This dissertation focuses on the domain and application area of engineering education. In this context, changes in engineering practices also begin to be reflected in engineering education [135], especially in the context of generative AI systems [136]. Overall, engineering education aims to equip students with the skills to tackle complex problems and adapt to evolving engineering practices [203]. However, as further described in more detail in Section 3.1, there is currently no unified understanding of domain-specific AI competencies within the engineering field. In addition, developing interdisciplinary programs and courses that integrate AI and engineering is challenging as educators face new demands for curriculum change.

Gap in Curriculum Change toward AI More broadly, there is also a gap in curriculum change toward AI education. In analyzing the external influences on curriculum change in higher education, Krause [163] concludes that there is a "need for focussed efforts to develop curriculum philosophy and scholarship to allow for an informed approach to defining, designing, and evaluating curriculum in its broadest sense, beyond the simple focus of a 'course'" (p. 47), particularly with respect to the conceptual frameworks and rigorous evaluation of the outcomes of curriculum change. As discussed in the state of the art Section 3.3, this is particularly evident in AI curricula and interdisciplinary curriculum development in the light of AI, where several recent studies position (interdisciplinary) curriculum development as a challenge [31, 57, 94]. With a focus on generative AI, Chiu [57] argues that more interdisciplinary teaching is needed and calls "future research [to] propose and assess new benchmarks and curricular frameworks for multidisciplinary or interdisciplinary teaching or programmes" [57, p. 8]. Thus, there is a need to investigate interdisciplinary approaches to AI education at the course and program level.

Closing the Gap Overall, this dissertation aims to address these gaps and conceptualize domain-specific AI competencies, propose and evaluate interdisciplinary curriculum development at the program level, and develop curriculum change support tools for educators. Thus, by addressing the domain-specific conceptualization and development of AI education in engineering education, it contributes significantly to the fields of AI education and engineering education.

1.2 Research Contexts and Goals

The following section provides an overview of the three main research contexts: AI competencies, curriculum development, and course development. First, an overarching system model of influences on programs, courses, and learning experiences at different levels is presented, before the research contexts are briefly introduced. These contexts are further detailed in the state of the art in Chapter 3.

1.2.1 Influences of Change in Higher Education Systems

To understand the research contexts of this work, it is important to take an overarching view of education systems with a focus on curricular innovation. Figure 1.1 illustrates the multi-level interplay of influencing factors that drive educational systems and curriculum innovation. It builds on several theoretical conceptualizations of curriculum innovation and influencing factors [104, 172, 174, 300].

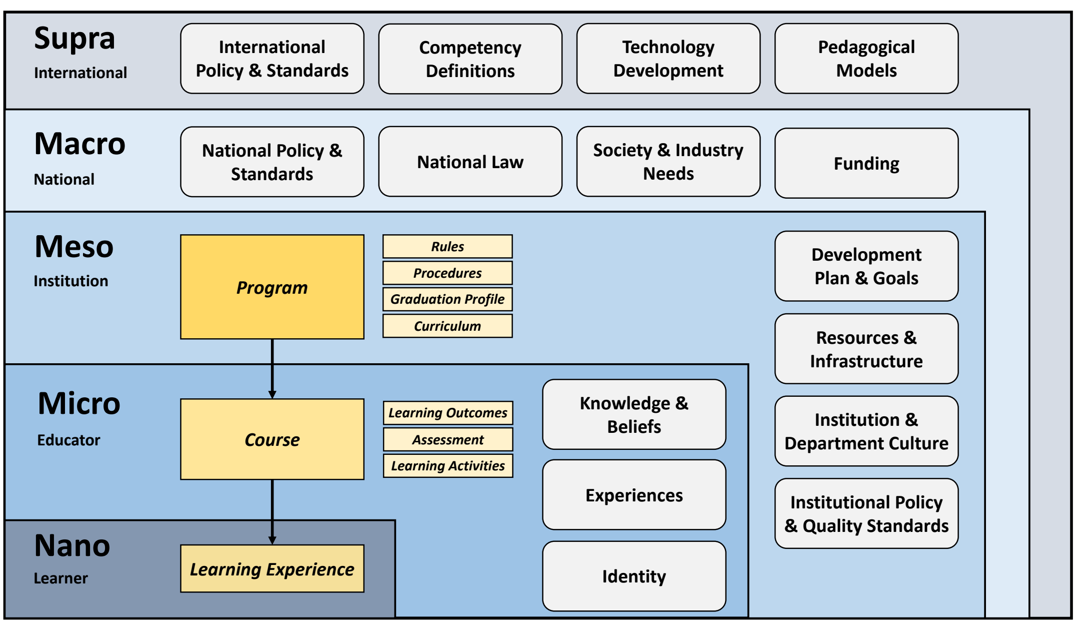

Figure 1.1: System model of influences on programs, courses, and learning experiences on different levels. The light gray boxes show influences along the levels, while the yellow boxes place the concepts of programs, courses, and learning experiences in these contexts.

The system model is organized into five distinct levels that contribute to or influence the design, implementation, and evaluation of educational systems and practices:

- **Supra Level (International)**: This level represents the global context and focuses on overarching influences such as international policies and standards, pedagogical models, and technological developments. These elements contextualize and influence the lower levels down to the institutional level or even individual courses. Examples are the efforts on policies and standards at the EU level, such as the Bologna reform, or the definition of digital competences [137].
- **Macro Level (National)**: The macro level addresses the national context, including influences such as national policies and laws, national quality standards, societal and industry needs, and funding mechanisms. These elements shape the broader regulatory and economic environment in which institutions operate. For example, institutions must comply with government standards at the national or state level. At the same time, development and innovation are often connected to specific government or external funding.
- **Meso Level (Institutional)**: The institutional level includes aspects such as institutional policies and quality standards, institutional and departmental culture, resources and infrastructure, and development plans and goals. Study programs as a concept are situated within an institution. Thus, an institution operates multiple programs that can be described by rules, procedures, a graduate competency profile, and a curriculum, but are also influenced by internal and external factors.
- **Micro Level (Educator)**: The micro level focuses on the perspective of the educator. Educators' curricular choices are influenced by external factors at the supra- or macro-level, internal factors in their institutions, but also individual factors of educators such as their knowledge and beliefs, experiences, or identity [172]. Courses take place at the educator level. A program consists of several courses, all of which are described by learning outcomes, assessment methods, and learning activities.
- **Nano Level (Learner)**: The nano level, as the most granular level, focuses on the individual learning experiences a learner has, for example, in a course. Influencing factors exist [89], but are not discussed here for simplicity, as this level is not addressed in the following.

The different levels influence each other. For example, technological developments such as AI may influence national policies and industry needs, or stimulate funding mechanisms. These may trigger new expectations in the graduate profiles of programs or be set in the development plans of institutions.

Contextualizing the Dissertation Overall, the dissertation addresses different perspectives and research contexts across the hierarchical levels illustrated in Figure 3.2. On the one hand, it explores the supra- and macro-level with a focus on the *what* question of conceptualizing what competencies are relevant for engineers working with AI. This includes addressing societal and industrial needs and informing international policies and standards, as well as graduate profiles. On the other hand, the dissertation focuses on the meso and micro level by investigating the *how* of adopting and integrating AI competencies in institutions at the program and course level, thus the operationalization of AI competencies. Specifically, it aims to develop curricula that can reflect the competencies and addresses how educators can be supported in integrating AI competencies into their disciplinary courses. In summary, by addressing the what and how questions at these interrelated levels, the empirical work of this dissertation provides a comprehensive perspective on integrating AI-relevant competencies into engineering education, linking global needs with practical applications at the institutional and individual levels. The system model (Figure 3.2) will be used throughout the dissertation to contextualize and connect the contributions across contexts.

The field of AI education is just emerging, especially in the domain application of engineering education. Therefore, the dissertation contributes to several research contexts, which are highlighted below.

1.2.2 Research Context: AI Competencies

Most education systems are competency-oriented, emphasizing the definition of competencies and learning outcomes that should be targeted [72]. This highlights the importance of understanding and anticipating which competencies will become relevant in the future [335]. In the specific context of AI, AI competencies describe what should be learned about AI and inform curriculum and course content choices.

There is a strong call to strengthen AI competencies in society, but also to integrate them across education [35, 129, 177]. Broadly speaking, AI competencies, also often referred to as AI literacy, can be described as “a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool in various settings, including online, at home, and in the workplace” [191, p. 2]. At the same time, to date, there is a wide variety of conceptualizations of AI competencies with no consensus reached [8, 177, 255]. As further contextualized in Section 3.2, AI competencies can be broadly categorized into generic, domain-specific, expert, and ethics-related AI competencies highlighting different levels and target groups [153].

In recent years, a focus has been on understanding the base construct of generic AI competencies [8, 153, 177], which refers to the competencies that everyone should acquire to critically interact with an AI system. In addition to generic, there is a particular domain-specific focus on AI literacy that recognizes that relevant AI competencies vary from domain to domain and that a transfer from generic to domain-specific applications is challenging [153, 255]. Although generic AI competencies have been the focus of research, the domain-specific contextualization of AI competencies has only just begun [153, 255].

Especially at a time when there is no established consensus on what constitutes AI competencies [8, 177], there is a need to conceptualize AI and its related competencies not only as a separate concept, but also in the context of different domains. As the use cases, the underlying data, and also the implications of using AI vary across domains and disciplines, it is essential to contextualize AI and related competencies in these domains, for example by reflecting industry needs [255]. This is further described as the conceptualization challenge around AI competencies in Section 3.1.

The dissertation aims to contribute to this challenge by establishing a conceptualization of domain-specific AI competencies in the context of engineering education. In particular, this conceptualization targets the overarching question of *how to conceptualize domain-specific AI competencies in the application domain of engineering*. To this end, Chapter 4 proposes statements of AI competencies for engineers based on competency clusters identified in interviews with eleven industry practitioners and the literature, and a content validity survey of 32 industry and academic experts.

1.2.3 Research Context: AI Curriculum Development

The second research context is the program level, specifically the focus on curriculum development. A curriculum can be described as a “plan for learning” [296] and operationalizes competencies. As described in the state of the art in Section 3.3, reflecting AI competencies in curricula in the context of domains is challenging for two reasons. First, curriculum development needs to reflect faster iterations of change to account for changing requirements [163, 318]. Second, there is a strong movement toward interdisciplinary programs that reflect the perspectives of multiple domains [240], especially the domain-specific view of AI education. At the same time, there is limited research on interdisciplinary curriculum development, making it challenging for educators and curriculum developers to take on the task [312]. Overall, more work and experience on a process and outcome perspective is needed to support, guide, and to some extent standardize the process.

The dissertation addresses the broad question of *how to develop and evaluate an interdisciplinary AI curriculum for engineering*. To this end, Chapter 5 focuses on both the process and the development outcome perspective by investigating a case study of an interdisciplinary curriculum development of a Bachelor's program on AI in engineering. Using a survey of 14 participants in the curriculum development and a self-evaluation of the facilitators, it provides insights into the effectiveness of the development approach. It also evaluates the outcomes of the development through a curriculum outcome mapping approach and focus group interviews with 19 participants from education and industry.

1.2.4 Research Context: AI Course Development

Educators are at the core of implementing the competencies and changing curricula and courses [172]. However, as further argued in Section 3.4, educators need to be supported in adopting curriculum changes, new content, and technologies.

This dissertation aims to develop a structured approach to support educators in integrating AI competencies into their disciplinary courses. In particular, it focuses on the overarching question of *how educators can be supported in integrating domain-specific AI competencies into their courses*. To this end, Chapter 6 investigates the development of the *AI Course Design Planning Framework* through a design-based research approach that includes multiple data collection using surveys (system usability scale, user experience scale, and others), observations in group discussions, and observation of outcomes while interacting with the design prototype. In total, over 100 educators interacted with the design prototype, while 29 participated in dedicated data collection workshops.

Overview of Research Objectives and Empirical Work To provide an overview of the research goals and empirical approaches in the different research contexts, Table 1.1 summarizes each research objective with the corresponding data collection, analysis, and outcomes.

Table 1.1: Overview on empirical contributions with respective research goals, data collection, analysis and outcomes.

Research Objective	**Data Collection**	**Analysis**	**Outcome**
Identify the challenges and gaps in integrating AI competencies into engineering education	Literature review and synthesis	Thematic analysis of literature	Systems perspective on integration of AI competencies in engineering education Synthesis of conceptualizations and operationalization of AI competencies Identification of challenges (*Chapter 3*)
Conceptualize domain-specific AI competencies in engineering	- Triangulation of interviews (11 industry practitioners) and literature - Survey (32 industry and academic experts)	Qualitative content analysis for competency clusters and content validity analysis for relevance and clarity of competency statements	Conceptualization of domain-specific AI competencies for engineers through 27 competency statements (*Chapter 4*)
Develop and evaluate an interdisciplinary AI curriculum for engineering	Analysis of a case study of curriculum development of an AI Bachelor program with multiple data collection: - Process: Survey of 14 participants and self-evaluation of facilitators; - Outcome: Focus group interviews (19 participants, education and industry) - Outcome: Curriculum outcome mapping	Descriptive analysis and qualitative content analysis through inductive coding	Insights into interdisciplinary curriculum development process and validation of an AI curriculum for engineering (*Chapter 5*)
Develop a structured framework to support educators in integrating AI competencies into their courses	Iterative design-based approach with multiple data collections: - Surveys (system usability scale, user experience scale, and others), - Observations in group discussions - Observation of outcomes while interacting with the design prototype (>100 interactions, 29 educators in detail)	Descriptive analysis and inductive coding of open questions, and outcomes	Design prototype of AI Course Design Planning Framework as a structural guide for educators to integrate AI competencies into their courses (*Chapter 6*)

1.3 Contributions

Situated in the emerging field of AI education and the application context of engineering education, the dissertation contributes to knowledge creation on both theoretical and practical levels. Section 1.3.1 summarizes the overarching research contributions. All contributions are further embedded in the state of the art in Section 3.5. In addition, Section 1.3.2 highlights the publications on which the work is based.

1.3.1 Research Contributions

The main contributions of the dissertation are as follows:

State of the Art on Education about AI The first major contribution of the dissertation is a comprehensive overview of the current challenges and developments in the integration of AI competencies with a focus on the application domain of engineering education. By synthesizing the existing literature, it lays the groundwork for understanding the complexities of the emerging field of education about AI in the context of higher education, focusing on curricular changes around AI and contextualizing the empirical work. However, the state of the art also contributes a novel conceptualization of AI competencies along the lines of generic, domain-specific, expert, and ethics-related AI competencies (Section 3.2). It also summarizes current efforts in teaching about and with AI (Section 3.3), with a particular focus on the role of the educator (Section 3.4) and provides a foundation for further research efforts.

Conceptualization of Domain-Specific AI Competencies for Engineering Building on the identified gaps in the conceptualization of bottom-up competency profiles for the domains [8, 153, 255], the dissertation introduces a conceptualization of domain-specific AI competencies for engineers. From a theoretical perspective, this conceptualization allows researchers to further develop domain-specific AI assessment tools for engineering education or to further contextualize AI competencies through a role-specific approach (Chapter 4). From a practical perspective, the conceptualization contributes to the operationalization and standardization of AI curriculum and course development in the engineering context and can be used by policymakers, curriculum developers, and educators.

Development and Validation of an Interdisciplinary Program for AI in Engineering The dissertation presents a conceptualization and validation of a process for developing an interdisciplinary study program in AI and engineering. It addresses the gap in curriculum change towards AI highlighted earlier [31, 57, 94] as well as the call for scholarship on curriculum beyond the focus on courses [163]. The empirical work focuses on the complexities of interdisciplinary curriculum design and implementation for AI programs, providing a structured process for program development and evaluation of outcomes (Chapter 5). It also highlights how participation in program development influences perceptions of quality and effectiveness.

Structural Framework for Educators to Integrate AI Competencies into Courses Recognizing the challenges educators face in integrating AI competencies into domain-specific courses, the dissertation contributes a structural guide designed to support educators in the development and co-creation of domain-specific AI courses. This structural framework aims to guide educators and curriculum developers in effectively integrating AI competencies into existing curricula and teaching practices (Chapter 6).

All practical contributions are available under an open license, allowing for reuse and adaptation. Links to these resources can be found in the respective chapters.

1.3.2 Publications

This dissertation includes several research papers published in various venues, conferences, and journals. An overview of all included papers is Table 1.2. Next to the articles mentioned in Table 1.2, further articles published that are not directly included in the dissertation are listed in Appendix B.1.

Table 1.2: List of published work sorted by chapters.

Chapters and Articles	**Key**
Chapter 3: State of the Art in Education about Artificial Intelligence	
Schleiss, J., Johri, A. & Stober, S. (2024). Integrating AI Education in Disciplinary Engineering Fields: Towards a System and Change Perspective. In: *Proceedings of 52th European Society for Engineering Education (SEFI) Conference*, 2126-2137.	[pub:18]
Klar, M.*, **Schleiss, J.*** (2024). Künstliche Intelligenz im Kontext von Kompetenzen, Prüfungen und Lehr-Lern- Methoden: Alte und neue Gestaltungsfragen. *MedienPädagogik: Zeitschrift für Theorie und Praxis der Medienbildung*, 58, 41-57.	[pub:6]
Decker, M., **Schleiss, J.**, Schultz, B., Moreno, S. G., Stober, S. & Leicht-Scholten, C. (2024). Towards Responsible AI-Competencies for Engineers: An explorative literature review on existing frameworks. In: *Proceedings of 52nd European Society for Engineering Education (SEFI) Conference*, 1372-1384.	[pub:2]

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Chapter and Articles	Key
Schüller, K., Rampelt, F., Koch, H., & **Schleiss, J.** (2023). Better ready than just aware: Data and AI Literacy as an enabler for informed decision making in the data age. In: *Informatik 2023 - Designing Futures: Zukünfte gestalten*, 381–384.	[pub:25]
Laupichler, M. C., Aster, A., Perschewski, J.-O., & **Schleiss, J.** (2023). Evaluating AI Courses: A Valid and Reliable Instrument for Assessing Artificial-Intelligence Learning through Comparative Self-Assessment. *Education Sciences, 13* (10).	[pub:8]
Schleiss, J., Mah, D.-K., Böhme, K., Fischer, D., Mesenhöller, J., Paaßen, B., Schork, S., & Schrumpf, J. (2023). Künstliche Intelligenz in der Bildung. Drei Zukunftsszenarien und fünf Handlungsfelder. *Berlin: KI-Campus.*	[pub:21]
Schleiss, J., Egloffstein, M., & Mah, D. K. (2024). Künstliche Intelligenz und Bildung in Deutschland: Erkenntnisse aus dem KI-Bildung Workshop 2024. In: *Proceedings of DELFI Workshops 2024.*	[pub:13]
Schleiss, J., Göllner, S. (2022). Rahmenbedingungen für Künstliche Intelligenz in Educational Technology. In: *Proceedings of DELFI Workshops 2022.*	[pub:14]
Chapter 4: An Interdisciplinary Competency Profile for AI in Engineering	
Schleiss, J., Bieber, M. I., Manukjan, A., Kellner, L. & Stober, S. (2022). An Interdisciplinary Competence Profile for AI in Engineering. In: *Proceedings of 50th European Society for Engineering Education (SEFI) Conference*, 1601-1608.	[pub:12]
Schleiss, J. & Johri, A. (2024). A Roles-based Competency Framework for Integrating Artificial Intelligence (AI) in Engineering Courses. In: *Proceedings of at 52nd European Society for Engineering Education (SEFI) Conference*, 2116-2125.	[pub:17]
Chapter 5: An Interdisciplinary Curriculum for AI in Engineering	
Schleiss, J., Manukjan, A., Bieber, M. I., Pohlenz, P., & Stober, S. (2023). Curriculum workshops as a method of interdisciplinary curriculum development: A case study for Artificial Intelligence in Engineering. In: *Proceedings of 51st European Society for Engineering Education (SEFI) Conference*, 1180–1189.	[pub:23]
Bieber, M., Manukjan, A., **Schleiss, J.**, Neumann, F., & Pohlenz, P. (2023). Die Nutzung der Curriculumwerkstatt im Rahmen der Curriculumentwicklung: Leitfaden und Fallbeispiel. In: *Handbuch Qualität in Studium, Lehre und Forschung*, 97–118.	[pub:1]
Manukjan, A., Bieber, M. I., & **Schleiss, J.** (2023). Über die Curriculumwerkstatt zum Curriculum. Betrachtung anhand eines neuen Studiengangs an der Schnittstelle zwischen Künstlicher Intelligenz und Ingenieurwissenschaften. In: *Proceedings of 10. Fachtagung Hochschuldidaktik Informatik (HDI 2023)*, 119-127.	[pub:9]
Schleiss, J., Manukjan, A., Bieber, M. I., Lang, S., Stober, S. (2025). Designing an Interdisciplinary Artificial Intelligence Curriculum for Engineering: Evaluation and Insights from Experts. [Manuscript submitted for publication]	[pub:22]
Chapter 6: Supporting Educators in Integrating AI Competencies in Courses	

Continued on next page

Table 1.2 – continued from previous page

Chapter and Articles	Key
Schleiss, J., Laupichler, M. C., Raupach, T., & Stober, S. (2023). AI Course Design Planning Framework: Developing Domain-Specific AI Education Courses. *Education Sciences*, 13 (9), 954.	[pub:19]
Schleiss, J., & Stober, S. (2023). Planning interdisciplinary Artificial Intelligence courses for Engineering Students. In: *Proceedings of 51st European Society for Engineering Education (SEFI) Conference*, 3249–3254.	[pub:24]
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1.4 Chapter Outline

The remaining work is organized as follows:

Chapter 2 focuses on providing a brief introduction to educational concepts. It defines and contextualizes the main concepts of the thesis, including competencies, learning taxonomies, and Open Educational Resources (OER). It also introduces the necessary foundations for curriculum development models and their evaluation, as well as the foundations for supporting educators in instructional design decisions.

Chapter 3 contextualizes the contributions of the dissertation through the different perspectives. First, Section 3.1 takes a broad systems perspective on the integration of AI competencies in engineering education and the underlying change mechanisms. Second, Section 3.2 contextualizes existing work on AI competencies and highlights the importance of developing domain-specific AI competency models. Third, Section 3.3 summarizes reference AI curricula and highlights work on implementing AI curricula across institutions. In addition, the section explores teaching about and with AI to contextualize the challenges educators face in their day-to-day work. Fourth, Section 3.4 puts the educator at the center and discusses the two demands that educators face - integrating AI competencies into their courses and adapting learning processes. Finally, all empirical contributions are contextualized in light of the current state of the art.

Chapter 4 conceptualizes domain-specific AI competencies for engineering. Based on literature and eleven interviews with industry experts, competency clusters are identified through qualitative content analysis. Competency statements are derived from these clusters and validated through a quantitative construct validity study with 32 experts from industry and academia.

Chapter 5 discusses a case study of the development of the Bachelor program in AI and engineering with a focus on the process of developing an interdisciplinary program. It provides insights into the development process through an ex-post survey of 14 participants and self-reflection of the three facilitators. In addition, the chapter evaluates the outcomes of the curriculum development through a mixed-methods approach using curriculum outcome mapping and focus group interviews with 19 educators and industry experts.

Chapter 6 proposes the development of the AI Course Design Planning Framework as a structural guide to assist educators in integrating AI competencies into discipline-specific courses. The chapter introduces the development approach through a design-based methodology and explores the evaluation in different workshops and settings.

Chapter 7 summarizes and discusses the results in the light of the state of the art. In particular, it highlights how the different parts contribute and build upon each other to integrate AI competencies in engineering education. The chapter highlights practical implications, provides recommendations, and suggests future research.

2
Background

This chapter provides a brief introduction to the background in education needed to understand the dissertation. Section 2.1 focuses on introducing the concepts of competencies, learning taxonomies, learning theories, and open educational resources. Section 2.2 highlights core theoretical approaches to curriculum development, and Section 2.3 introduces instructional design frameworks as a means of supporting educators.

2.1 Concepts and Definitions

Competencies

The development of competencies is one of the central goals of education. However, even within the educational community, there are different ideas and definitions of competencies [326, 339]. A comprehensive discussion on different streams and definitions can be found in [339], [315], and [326].

The term *competency* is often used interchangeably with associated terms such as skill, ability, and literacy [56]. However, there is a nuanced but important distinction arguing that competencies go beyond knowledge and skills to include attitudes and values. For example, in the context of the OECD *Education 2030 Framework* [244], the OECD positions a competency as "the ability to mobilize knowledge, skills, attitudes, and values, alongside a reflective approach to the processes of learning, in order to engage with and act in the world."[244, p. 2]. Similarly, in their conceptualization of key competencies for lifelong learning, the *European Commission* positions competencies as a combination of knowledge, skills, and appropriate attitudes for a given context [85, p. 5]. Vitello et al. [315] describe competency as "the ability to integrate and apply contextually-appropriate knowledge, skills and psychosocial factors (e.g., beliefs, attitudes, values, and motivations) to consistently perform successfully within a specified domain" [315, p. 4]. This is in line with Tuomi [307] who proposes to view competencies as the "capability to get things done" [p. 605] and to distinguish between an "epistemic component that includes knowledge, domain-specific skill and experience" [p. 604] and "non-epistemic elements [which] capture many of the things commonly called transversal, generic, or core competences and skills" [307, p. 605]. Overall, the different notions of competencies highlight the breadth of possibilities in describing and defining them.

In the context of competency orientation in education, Germany has adopted the *European Qualification References Framework* to provide a regulatory foundation and orientation for students, educators, and educational institutions, forming the *German Qualifications Framework for Lifelong Learning* [72]. In this context, the framework provides a somewhat more nuanced view that addresses professional, methodological, social, and self-competencies [72]. These facets also form the foundation for *German Higher Education Qualifications* [166].

Connecting to the different notions described above and aligning to the German Qualifications Framework for Lifelong Learning, the term competencies is used in the following work as the ability to act in and cope with context-specific demands [273]. Following [273], we can roughly distinguish four categories of competencies:

1. *Professional competencies* describe the specific knowledge, skills, and experience to perform the professional function.
2. *Methodological competencies* represent cognitive skills that can be applied across situations and are required to deal with complex tasks and problems.
3. *Social competencies* characterize the knowledge, skills, and abilities to achieve goals in social interactions.
4. *Self-competencies* describe skills and psychosocial factors that relate to a person's self-awareness and behavior and influence their work practices.

Learning Outcomes and Taxonomies

Another way to categorize and organize competencies is the use of learning taxonomies of learning outcomes. A learning outcome is a specific and measurable statement that articulates what students should know, be able to do, or value upon completion of a learning experience. As such, learning outcomes guide the learning experience and support educators and students alike by providing explicit goals.

Learning taxonomies describe different levels of complexity of learning outcomes. One of the best-known taxonomies is Bloom's Taxonomy [27, 162], which classifies cognitive skills into six levels: remembering, understanding, applying, analyzing, evaluating, and creating. Another proposed taxonomy is the Structure of Observed Learning Outcomes (SOLO) taxonomy [22], which provides a systematic framework for assessing the depth of student understanding and guiding educators in designing learning experiences that promote deeper comprehension. In summary, taxonomies can guide educators in addressing different levels and aligning instructional strategies with the desired learning outcomes.

Engineering Education and Engineering Education Research

Engineering education aims to prepare engineering students to solve complex problems and to be prepared for engineering practice [203]. In this context, the field of Engineering Education Research (EER) aims at generating a "systematic understanding" [33, p. 19] of how to improve engineering education. This systematic understanding requires efforts that are both practical, to influence engineering education practice, and scholarly, to advance the application of educational theory within the engineering context [79]. Malmi et al. [201] described EER as "a field, which seeks to (1) build deep understanding of student learning in engineering sciences, (2) identify theoretical underpinnings for innovations in engineering education and (3) evaluate these innovations to build empirical evidence and better understanding of their impact on students' learning processes and learning outcomes. Thus EER aspires to study the complex interactions between the central actors in the learning process, that is, students, teachers, teaching organisations and external stakeholders, as well as their relation to subject content." [201, p. 171]. This highlights the interdisciplinarity of EER as well as the diversity of perspectives and stakeholders [312].

Open Educational Resources

OERs can be described as "educational materials which use a Creative Commons license or which exist in the public domain and are free of copyright" [332, p. 783]. This includes various forms of materials and allows for what Wiley has coined the *5Rs* (Retain, Reuse, Revise, Remix, and Redistribute) [url:15]. The respective licenses vary in terms of permissions and restrictions. For example, some licenses may impose conditions that limit how resources can be used, such as prohibiting commercial use or requiring that derivative works adopt the same license. Thus, OERs end where restrictive licensing begins [332]. In addition, resources that require payment or restrict access fall outside of OERs.

The practices of creating OERs but also sharing other practices are discussed under the term *Open Educational Practices (OEP)* [62]. However, the "conceptualisations of OEP vary widely, ranging from those centred on the creation and use of OER to broader definitions of OEP, inclusive of but not necessarily focused on OER" [62, p. 128]. This variability reflects the different approaches to open education and its implementation in different contexts. Even though not central in this work, the concepts of OER and OEP can be embedded in instructional practices of AI education as explained in Chapter 6.

Use of Theories and Frameworks

In an educational context, theories are frameworks of interrelated concepts that organize and condense knowledge about specific phenomena [232]. They serve as systematic approaches that clarify observations and help to understand the complexities of the world [95]. Theories aim to provide coherent explanations for observed behaviors, facilitating a deeper understanding of complex social dynamics. They also help situate findings within existing academic conversations, showing how new insights build on or transcend previous work [134].

The following sections discuss learning theories, curriculum theories, and instructional models. *Learning theories* focus on how individuals acquire, process, and retain knowledge and guide educators in developing effective instructional strategies. *Curriculum theories*, on the other hand, provide a framework for understanding how curricula are designed, implemented, and evaluated. They explore the philosophical and theoretical underpinnings of educational content and structure to ensure that curricula are aligned with desired learning outcomes and societal needs. *Instructional Models* bridge learning and curriculum theories by offering practical approaches to teaching that reflect theoretical principles. These models help educators translate abstract theories into concrete practices and ensure that instructional strategies are effective and relevant for diverse learners.

Learning Theories

There are several schools of thought about conceptualizing learning, each with its own assumptions and focus (see Table 2.1). In order to contextualize the dissertation, a brief overview of the main strands and schools of thought is given below. It is important to note that theories are usually not used in isolation, but help to inform the development of effective educational strategies. For more details, please refer to the related textbooks and articles [83, 278].

Table 2.1: Exemplar learning theories.

Learning Theory	**Description**	**View on Learning**
Behaviorism	Focuses on observable behaviors and responses to stimuli	Learning as a change in behavior as a result of experience
Cognitivism	Focuses on mental processes in processing, storing, and retrieving information	Learning as an internal process of acquiring and organizing knowledge
Constructism	Emphasizes that learners construct their own understanding through experience	Learning as an active process of constructing meaning
Social Learning Theory	Focus on the importance of observing and modeling the behaviors of others	Learning occurs through social interaction and imitation
Humanism	Focuses on the self-actualization and personal growth of the learner	Learning as a holistic process that addresses psychological and emotional needs
Connectivism	Recognizes the role of technology and networks in the learning process	Learning as a process of connecting information from a distributed network of connections
Experiential Learning Theory	Emphasizes learning through direct experience and reflection on that experience in a cyclical process	Learning as a continuous process based on experience that requires reflection, conceptualization, and active experimentation
Adult Learning Theory	Focuses on how adults learn differently from children, emphasizing self-direction and practical application	Learning as a self-directed process drawing on life experience and focused on immediate problem-solving

Behaviorism At its core, behaviorism focuses on conditioning by environmental responses to the learner's actions [286]. It emphasizes the observable behavior of learners and treats mental processes as unknown. Knowledge is seen as a repertoire of behavioral responses to stimuli learned through repetition and positive and negative reinforcement by an authority, e.g., the teacher.

Cognitivism Cognitivism explicitly focuses on the internal, mental processes and cognitive structures involved in processing information and compares learning to a computational model of information processing [83, 278]. It assumes that there is an objective truth that a learner can internalize. Long-term memory represents a mental representation of the world that becomes better aligned with the actual world through learning experiences.

Constructivism Constructivism critiques this more passive view of learning and presents a view of the learner as an active constructor of his or her own unique knowledge. According to constructivist learning theory, learners bring their own knowledge and perspectives that have been constructed in previous learning situations and influence the learning process [91].

Social Learning Theory Social learning proposes that learning occurs through observation and imitation at all times [15]. It focuses on the give-and-take interaction between social, cognitive, and environmental influences. In contrast to behaviorism, where learning is influenced by reinforcement and punishment, this model suggests that observing others being rewarded and punished can indirectly influence behavior [15].

Humanism Humanistic learning theory, developed in the 1960s by psychologists such as Carl Rogers and Abraham Maslow, places the individual at the center of the learning process. The theory emphasizes personal growth, self-direction, and the inner drive for self-actualization [268]. For example, Rogers argued that significant learning takes place when the subject matter is relevant to the personal interests of the learner and when the learning environment supports personal growth without threatening the self-concept [268].

Connectivism Connectivism emerged as a "learning theory for the digital age" [282]. It argues that in today's digital world, learning is no longer an internal, individualistic activity, but rather occurs through connections within networks, with technology serving as a facilitator of learning [282]. It thus recognizes that learning occurs within a network of connections influenced by technology and socialization.

Experiential Learning Theory Experiential learning theory proposes a cyclical model of learning through abstract conceptualization, concrete experience, active experimentation, and reflective observation [157]. The theory builds on the work of John Dewey, Kurt Lewin, and Jean Piaget and emphasizes that "learning is best conceived as a process, not in terms of outcomes" [156, p. 6].

Adult Learning Theory To explain the differences in learning between adults and children, Knowles formulated the theory of andragogy [154]. This theory emphasizes that adult learners are self-directed, draw on their life experiences, focus on problem solving rather than content, and are internally motivated to learn [154].

2.2 Curriculum Theories and Development

After exploring different views of learning and establishing key concepts, this section focuses on the foundations of curriculum, curriculum development, and curriculum evaluation. This section builds the foundation to the curriculum development process and evaluation, described in Chapter 5.

2.2.1 Understanding Curriculum

Definitions of Curriculum The concept of a curriculum has different definitions and conceptions [195]. It is referred to as content as in what is studied [253], learning experiences and plan for learning [296], communication of objectives [27], or plan for instruction [98]. Another stream is non-technical approaches that take a broader conception of curriculum into more philosophical matters, arguing for curriculum as a "living organism as opposed to a machine which is precise and orderly" [195, p. 6].

In the context of this dissertation, the brief definition of Hilda Taba [296] is followed, which describes curriculum as a "plan for learning". Consequently, curriculum is understood as the overall plan of modules and student experiences in an educational program, serving as the normative basis for the content and methods of a study program. This concept is also reflected in the German translation of the term as "Lehrplan".

Curriculum Levels To better understand curricula and related activities, it is useful to distinguish between levels of a curriculum [300]. According to the established levels (Figure 1.1), different types of curricula can be identified. On the supra-level there are international guidelines or comparative studies (e.g., the OECD standardized literacy tests). At the macro level, representing the system, society, or state, there are national curricula, core objectives, or accreditation goals. Institutional curricula and individual programs are at the meso level. These consist of several courses that also have their own curriculum. The lowest level, the nano-level, is the personal or individual curriculum, which refers to the learner's own learning path. This dissertation partly addresses the supra- and macro-level when identifying relevant competencies for engineers working with AI (Chapter 4), the meso-level through the case study of interdisciplinary curriculum development (Chapter 5), and the micro-level when supporting educators in designing domain-specific AI courses (Chapter 6).

Curriculum Representations To understand curriculum evaluation, it is useful to understand different curriculum representations. Goodlad [97] proposed six forms of curriculum, which Thijs and van Akker consolidated into three main forms [300]. An overview is given in Figure 2.1.

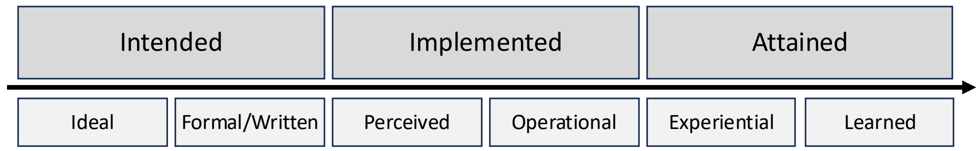

Figure 2.1: Curriculum representations based on [97, 300].

The *intended curriculum* refers to the curriculum developed and designed by the curriculum developers. It is described by the ideal curriculum, which describes the vision as the rationale or basic philosophy, and the formal or written curriculum, which refers to the stated intentions in curriculum documents and other materials. Second, the *implemented curriculum* is the curriculum that educators implement in practice. It consists of the perceived curriculum, as it is interpreted by educators, and the operational curriculum, which refers to the actual process as in the curriculum in action. Third, the attained curriculum refers to the curriculum that learners have attained from the implemented curriculum. Further subdivisions here are the experimental curriculum, which describes the learning experiences perceived by the learners, and the learned curriculum, which refers to the resulting learning outcomes of the learners.

Clarifying which representation is targeted and evaluated is useful for analysis and comparative studies, especially given the effects and differences in the curriculum of each representation from intention to implementation to attainment. Chapter 5 focuses on the intended curriculum by analyzing the formal and written curriculum of the case study using a formative evaluation.

Curriculum Elements A curriculum has different elements that are related to each other (see Table 2.2). These relationships can be illustrated by the curriculum spider web [5], which shows that they all influence each other.

Curriculum Influences As highlighted in the introduction and in Figure 1.1, a curriculum takes place in a socio-cultural context and is therefore influenced by internal, external, and individual aspects [163, 172, 174]. These may include external influences such as labour market, accreditation, and quality mechanisms, as well as internal influences such as institutional culture, faculty background and experience, and leadership [163, 172, 174]. This also highlights the different stakeholders of a curriculum with a range of interests and motivations [138]. The influences are further contextualized with respect to AI education for engineering in Section 3.1.

Table 2.2: Elements of a curriculum [5], with components and guiding questions towards the students in the curriculum.

Component	Guiding Question
Rationale	Why are they learning?
Aims and objectives	Towards which goals are they learning?
Content	What are they learning?
Learning activities	How are they learning?
Teacher role	How is the teacher facilitating their learning?
Materials and resources	With what are they learning?
Grouping	With whom are they learning?
Location	Where are they learning?
Time	When are they learning?
Assessment	How is their learning assessed?

Curriculum Design Theories The choice of how to structure a curriculum also underlies values and understandings of learning. Curriculum design is concerned with how the different elements of a curriculum interact and are balanced [246, p. 184]. At a broad level, we can distinguish between subject-centered designs, learner-centered designs, and problem-centered designs [246]. *Subject-centered* designs implement core curricula around specific content, often defined at the state or national level. *Learner-centered* designs place the learner, with his or her individual needs and requirements, at the center of curriculum development. Finally, *problem-centered* designs structure the curriculum around problems and focus on building the skills to solve them. In summary, each approach represents different perspectives on how learning should be structured and what outcomes should be prioritized in education. These are reflected in the curriculum development models.

2.2.2 Curriculum Development Models

According to Ornstein and Hunkins [246], the idea of curriculum development is "to show how [a] curriculum is planned, implemented, and evaluated as well as what people, processes, and procedures are involved in constructing the curriculum" [246, p. 30]. The following section covers the core activities of development, a differentiation of development approaches, and practical considerations.

Core Activities Scholars have proposed various frameworks for curriculum development, each with its own emphasis and underlying assumptions. The five core activities common to all models include analysis, design, development, implementation, and evaluation. These may be familiar from the instructional design model

Analyze, Design, Develop, Implement, and Evaluate (ADDIE) [37]. Different development approaches can be distinguished by the way in which they focus on these core activities.

Overall, approaches can be differentiated into technical and non-technical approaches [246], where the technical approach refers to a rational approach to delivering education with a focus on logic, effectiveness, and efficiency. On the other hand, the non-technical approach focuses on the learner. Other authors also use the distinction between a product model and a process model, with the product model focusing on outcomes and the process model focusing on methods and learning activities [231, 241]. For a more nuanced view, we follow the four types proposed by Visscher-Voerman and Gustafson [314], grouping them into instrumental, communicative, artistic, and pragmatic approaches.

Instrumental Approach This approach emphasizes systematic planning and focuses on clearly defined goals and objectives. It follows a linear, step-by-step process that moves through the design in a logical sequence.

Examples of this approach include the models of Tyler, Wheeler, and Taba models, as well as backward design and the task analysis model. The model developed by *Tyler* in 1949 [308] places emphasis on defining objectives, selecting appropriate learning experiences, organizing them, and evaluating progress. It is considered systematic and rational-linear with an emphasis on setting behavioral goals and measuring them through assessment [300]. The model is teacher-centered and prescriptive, meaning that educators decide the learning goal and structure the learning experiences accordingly. Overall, the Tyler model has influenced many curriculum design projects, and its objectives-based approach fits well with the competency orientation of the Bologna reform in Europe.

As an improvement to Tyler's linear model, *Wheeler* proposed a cyclical process consisting of five interrelated stages that allow for ongoing refinement and adaptation [327]. The model emphasizes the iterative, continuous process of curriculum development. Similarly, *Taba* [296] advocates an inductive approach in which educators begin by creating specific educational units based on identified needs and then move toward broader curricular considerations. With its focus on educators, it is often considered a grassroots approach. Another model is the *Backward Design* [330], which emphasizes starting at the endpoint of the desired learning outcomes and working backward to learning activities and topics. It is a variation of the *Task Analysis Model*, which focuses on identifying the relevant skills and related content needed to accomplish a real-world task. Overall, critics argue that the instrumental approach can be too rigid and may not account for the complexities of real-world learning environments and the changing needs of learners [300].

Communicative Approach The communicative approach emphasizes collaboration, deliberation, consensus-building, and stakeholder involvement throughout the design process. At its core, it recognizes that curriculum development is a social and political process, not just a technical one. One prominent example of the approach is the *deliberative model* proposed by Walker [319]. The model focuses more on the complex practices of negotiations going through three phases. First, in the phase of the so-called platform of ideas, stakeholders present their views and opinions aiming for consensus. Second, in the deliberation phase, participants generate solutions for the identified problem. Third, the design phase transforms the results of the previous phase into a draft product. Other approaches might include *participatory design methods* that emphasize including the voice of multiple stakeholders [64, 161].

An advantage of the communicative approach lies in the participatory aspects of it leading to stronger support for the final outcome. At the same time, the approach is often time-consuming and may lead to compromises or not internally consistent products [300].

Artistic Approach The artistic approach views curriculum development as a creative, intuitive process rather than a purely rational one. The process is completely open with no objective criteria or fixed procedures but rather an emphasis on the role of the designer's vision and expertise. One example of this approach is the model of *Eisner* [81] that focuses on holistic and creative reflection of aspects of the curricula and puts teachers in a central role in making decisions based on their vision and experiences. The model puts a focus on envisioning and meeting the needs of the students in a particular context while emphasizing that there are multiple ways in which people learn and learning processes are enacted [246]. Another example is *Slattery's model* [287] that emphasizes creativity, interpretation, and the integration of various perspectives. An important aspect is the role of the educator as a creative and critical practitioner rather than merely an implementer of predetermined content. The artistic approach has its strength in developing innovative, experimental curricula in a particular context. However, it lacks rigorous evaluation and can be subjective to the designer's judgment and experience [300].

Pragmatic Approach This approach emphasizes practical usability and iterative development together with users [300]. It focuses on flexibility, rapid prototyping, and ongoing revision based on real-world feedback using tools and methods from *Design Thinking* [44]. At its core stands a cyclical development with frequent formative evaluations together with the target audience. The pragmatic approach is often used in technology-enhanced learning environments or in situations where the learning context is rapidly changing and requires frequent updates to the curriculum. Examples include *rapid prototyping method*s and *agile development approaches* adapted for education (e.g., [100]). A downside of the approach is that it can lead to a lack of overall coherence in the curriculum, especially when the demands and wishes of users do not align with the insights of experts and literature.

Curriculum Development in Practice In summary, each of these approaches offers different strengths and is suited to different contexts. In practice, curriculum developers may combine elements from multiple approaches depending on their specific needs and constraints. This is highlighted by the three different paths of curriculum development in higher education proposed by Schaper et al. [273]. The authors distinguish between the use of existing guiding principles and educational standards or competency profiles, second, surveying graduates of comparable study programs and subject-specific employers, and third, participatory methods for the development of novel and non-comparable degree programs. As discussed later in Chapter 5, the presented case study also used a participatory approach in combination with the instrumental approach of Backward Design.

2.2.3 Curriculum Evaluation

Evaluating the quality of a curriculum is a complex undertaking. Two main types of evaluation can be conducted [238]: *formative evaluation* during development to refine and improve the program, and *summative evaluation* to assess the effectiveness of a program and help decide whether to continue or discontinue a program. The following focuses on a formative evaluation to assess the development outcomes.

Quality Criteria In this context, Nieveen proposed the following quality criteria [238]:

- **Relevance**: The intervention is needed and its design is based on the latest scientific research.
- **Consistency**: The curriculum structure is logical and coherent.
- **Practicality**:
  - *Expected Practicality*: The intervention is expected to be readily applicable in the intended settings.

  - *Actual Practicality*: The intervention can be used successfully in the intended settings.
- **Effectiveness**:
  - *Expected Effectiveness*: Use of the intervention is expected to result to the desired outcomes.
  - *Actual Effectiveness*: Implementing the intervention actually leads to the desired outcomes.

The actual practicality and effectiveness can only be evaluated during or after the implementation. Thus, in the context of validating the developed curriculum (Chapter 5), the focus is on the expected practicality and effectiveness along with consistency and relevance.

Methods of Formative Evaluation Different approaches are proposed in the context of formative evaluation of curricula [238, 298]:

- **Screening**: Characteristics of the prototype are evaluated by the research team using checklists.
- **Expert Review**: Prototype of intervention is reviewed by a group of experts (e.g., subject matter experts, instructional designers, educators), typically using a guide with key questions from the design research team, often through interviews.
- **Walk-through**: The intervention is reviewed together with a few users from the target group, usually in a face-to-face setting.
- **Micro-evaluation**: Parts of the intervention are used by a small group of the target audience (e.g., learners or educators) with the evaluator acting as an observer and interviewer.
- **Try-out**: Materials of intervention are used in a normal life setting by a limited number of users. This can focus on evaluating the practicality through observation, interviews, logbooks, and questionnaires or the effectiveness of using learning reports and/or tests.

These methods have different usefulness depending on the design phase, see [238, 300] for a detailed overview. In the context of Chapter 5, screening and expert review are used.

2.3 Supporting Educators in Instructional Design

While curricula are often part of a broader design and supported by curriculum developers, educators operate and operationalize them in courses. Thus, on the micro-level, educators are involved in providing instruction and guidance to their students. These decisions are influenced by the educator's beliefs and understanding of learning, and the role educators can take to facilitate it [172].

Multiple scholars have proposed guidance for educators in their course design, which can be broadly categorized in *instructional design frameworks* targeting how to create instruction, and *instructional design methods* targeting specific techniques or strategies for implementation of instruction. With one focus of the dissertation laying on the process of supporting educators in the design of their courses or more specifically in integrating AI competencies in the context of their disciplines, the following introduces instructional design frameworks that provide the foundation and context for Chapter 6.

Instructional Design Frameworks

Instructional design frameworks, sometimes called design models, are the process guides that help educators develop their courses. They provide a process and development perspective, that can be followed to achieve targeted outcomes.

ADDIE *ADDIE* is short for *Analyze*, *Design*, *Develop*, *Implement*, and *Evaluate*, and is a framework for organizing the steps in instructional design [37]. The steps are described as follows [37]:

- *Analyze*: Gather information about learner needs, expectations for the course, resources needed, and instructional objectives.
- *Design*: Establish learning objectives, select instructional methods, and choose delivery methods.
- *Develop*: Create and validate learning resources.
- *Implement*: Distribute and monitor learning resources to students.
- *Evaluate*: Evaluate the quality of implementation and results.

While the steps refer to different phases, the framework reinforces the need to evaluate and test the results of each phase and to iterate across phases.

Successive Approximation Model *Successive Approximation Model (SAM)* was developed as an alternative to ADDIE as an agile approach to instructional design [7]. It emphasizes iterative development and rapid prototyping, allowing for continuous feedback and improvement throughout the design process. At its core, it consists of three phases: (1) the *preparation phase* for information gathering, (2) the *iterative design phase*, which begins with a collaborative brainstorming session and continues with iterations through design, prototype, and review, and (3) the *iterative development phase*, which focuses on iterations through development, implementation, and evaluation. Through the iterative process, the SAM model promises agility and flexibility in course development based on learner and stakeholder feedback.

Kemp Instructional Model Another nonlinear model is the Kemp model [144]. It has nine interrelated elements: *instructional problems*, *learner characteristics*, *task analysis*, *instructional objectives*, *content sequencing*, *instructional strategies*, *designing the message*, *instructional delivery*, and *evaluation instruments* [144]. The nonlinear structure emphasizes that these elements can be addressed in any order, individually, simultaneously, or also not at all.

Dick and Carey Model In this model, the starting point is *identifying instructional goals*, which defines what learners are expected to achieve. Next, *conducting instructional analysis* breaks tasks down into specific steps, helping educators understand what is needed for learners to succeed, and *analyzing entry behaviors* assesses learners' prior knowledge and skills, ensuring that instruction is tailored to their needs. This is complemented by the *formulation of performance objectives*, which specifies measurable outcomes for learners. The model then emphasizes the *development of assessment tools* to evaluate learner progress, as well as the *development of instructional strategies* and related *instructional materials*. *Formative evaluation* is used throughout the process to identify areas for improvement, while ongoing revision of instruction ensures adaptability to learner feedback, while *summative evaluation* assesses the overall effectiveness of the instruction. Overall, the model also emphasizes revision of instruction based on all components.

Backward Design Backward design is a design model applicable to curricula and courses [330]. At its core, it describes the idea of starting with the end in mind. That is, identify the desired learning outcomes, establish points of assessment that can determine whether the outcomes have been achieved, and design activities that will lead to their achievement.

Design Considerations In addition to models, broad design considerations include *constructive alignment* [21], which describes the alignment of learning outcomes, assessment, and instructional methods to enable student learning. Similarly, *Merrill's Principles of Instruction* [214] emphasize the importance of real-world problem solving, activation of prior knowledge, demonstration of skills, application in context, and integration of knowledge into everyday life.

Summary Overall, these models provide structured processes for developing instruction and integrating competencies. Particularly relevant for this work is that all models include a thorough need analysis to define the relevant learning objectives. With the current pace of AI development and changes in technological capabilities, it is even more important to define the learning objectives and have measures of rapid iterations in place. At the same time, especially in the context of disciplines, identifying the relevant AI competencies and developing a coherent learning experience around them is a challenging task for educators. In the following chapter, these challenges are further contextualized within the current state of the art on education about AI. Moreover, Chapter 4 discusses relevant competencies in the context of engineering. Chapter 5 focuses on curriculum development at the program level, while Chapter 6 presents a supporting framework that builds on instructional design frameworks and can be used to assist educators in their development of AI education courses.

3 State of the Art in Education about Artificial Intelligence

Having established the core educational foundations, the following chapter lays the foundation of the dissertation. It begins by exploring the systems perspective on the integration of AI competencies. In particular, Section 3.1 discusses curriculum change and the various influences on curriculum change from external, internal, and individual perspectives. This provides the basis for highlighting the key challenges in integrating AI competencies in engineering education (cf. Section 3.1.5).

The following sections then explore related work on these challenges. Specifically, Section 3.2 describes the current understanding of AI-related competencies and introduces relevant perspectives and frameworks. It presents a novel perspective on AI competencies that distinguishes between generic, domain-specific, expert, and ethics-related AI competencies. Section 3.3 focuses on the operationalization of AI competencies in curricula and courses, while Section 3.4 contextualizes the role of educators. Finally, Section 3.5 highlights the contributions of the dissertation in the context of the state of the art.

Overall, this chapter serves as a foundation and contextualization for the contributions of the dissertation. However, it also includes work from several research articles [pub:2, pub:6, pub:18, pub:25] and contributes a systems perspective on the integration of AI competencies, a novel contextualization of AI competencies, and an overview of the current state of the art in AI education with a focus on the role of educators, making it a significant contribution to the field of engineering education and AI education.

3.1 System Perspective on Integrating AI Competencies in Engineering Education

Building on existing research on curriculum change, this section highlights a systems perspective on the integration of AI education in engineering by analyzing perspectives from interdisciplinary engineering education, internal and external drivers of program-level change, and change theory. In particular, it is guided by the question: what factors - external, internal, and individual - influence the integration of AI competencies in engineering education? These theoretical and conceptual lenses of influence also provide the basis for identifying current challenges to the integration of AI competencies in engineering education before delving deeper into how they are being addressed in the current state of the art.

This section builds on and extends an article [pub:18] published at the annual conference of the European Society for Engineering Education (SEFI) in 2024. First, Section 3.1.1 contextualizes AI education in engineering. Second, Section 3.1.2 examines aspects of program and curriculum development, focusing specifically on an interdisciplinary perspective. Next, Section 3.1.4 introduces the system model of influences with its respective levels. Finally, Section 3.1.5 summarizes the main challenges in integrating AI competencies in engineering education from a system perspective.

3.1.1 Contextualizing AI Education in Engineering

The use of AI has become increasingly relevant across domains [107, 250]. The rise of generative AI tools in particular is an example of how the use of AI-based tools, such as Large Language Models (LLMs), have found high use, especially by students, while research indicates that to date students' conceptual understanding of how these tools work is limited [305, 324]. At the same time, engineering practices have changed over time towards more digital practices where AI increasingly plays a role [11, 25, 29]. Thus, the digital transformation accelerated by AI increases the need for AI education in the disciplinary context so that students can make responsible judgments about the use of tools, the outputs they get, and that they are workforce-ready [52, 74].

Positioning AI Education AI education can be defined from multiple perspectives. First, it describes teaching about AI rather than the use of AI tools in teaching and learning [343]. While the adoption of tools for teaching and learning, such as LLMs, has received considerable attention [31], the integration of AI competencies into engineering education is lacking. Second, AI education can address different target groups, distinguishing between *generic, basic AI literacy competencies* that build foundations for the general public, *domain-specific AI competencies* in the context of a discipline, and *expert AI competencies* that target advanced methodologies, next to overarching *ethics-related AI competencies* [153, 177, 191, pub:19]. Third, AI education in engineering education can be seen as a subset of CS education, similar to the role of programming, which is a foundational skill but applicable across disciplines, requiring a greater understanding of how it can be integrated into curricula [202].

Integrating AI Education into Disciplinary Engineering Fields With the premise that the use of AI tools and applications will become more dominant across different engineering use cases, it is necessary to address the integration of related AI competencies in the engineering curricula and create systematic research-based understanding. This aligns with the call for interdisciplinarity in engineering education aimed at integrating multiple disciplines to solve a problem [289, 312], as well as the continuation of efforts towards digital engineering and the use of data and computation in engineering [52].

3.1.2 Interdisciplinary Curriculum Development and Change

According to Lattuca and Stark [174], a program, or as they call it an academic plan, includes purpose, content, sequence, instructional processes and resources, assessment strategies, and approaches to evaluating programs or courses [145, 174]. It also includes a feedback loop that accounts for changes that educators make after receiving feedback on a course or program. Thus, a program has content aspects (curriculum) and organizational aspects (regulations). On the content side, a curriculum is usually described by the goal, purpose, content, and sequence of how different modules work together (see Section 2.2). Different modules may consist of one or more courses and include instructional resources, processes, assessment, and evaluation, all aimed at building competencies for learners.

Curriculum Development Curriculum development and change in higher education has been less studied than in school education [302], possibly because of the barrier of "cumbersome, inflexible, and lengthy administrative processes" [126, p. 639] and the difficulty of promoting content change in the educational system [138]. Overall, curriculum change can be understood as the change of one or more elements of the program [172].

Interdisciplinary Perspective When discussing AI competencies in engineering education, it is also necessary to integrate the interdisciplinary perspective on curricula and competencies. Interdisciplinary engineering education is based on the idea of bridging the different epistemologies of disciplines and integrating content and concepts from different disciplines into one teaching approach [186, 289, 312]. It is often built with the vision of developing competencies for complex real-world situations, such as collaboration or communication [173, 186, 312] and in turn increase the employability of future engineers [106]. Moreover, interdisciplinary teaching should improve disciplinary programs and student motivation [186, 312]. The understanding of interdisciplinarity is relevant for the following work, as it frames the competencies that lie at the intersection of AI and engineering, as well as the process and outcome of curriculum design.

Interdisciplinary Curriculum Design Interdisciplinary study programs vary in their curriculum and organization, which distinguishes them into strong and weak interdisciplinary programs [13, 150, 152]. A key differentiator is the emphasis on integrating knowledge. Research on interdisciplinary curriculum design suggests that interdisciplinary knowledge is less clearly classified than discipline-based knowledge [217], which Muller [227] links to a limited depth of knowledge that students encounter in interdisciplinary curricula. This suggests that interdisciplinary curriculum development requires a careful balance between breadth and depth [14, 26]. In this context, Millar [218] calls for a more critical analysis of curriculum changes from discipline-based to interdisciplinary curricula.

Knight et al. [152] found that indicators of strong program interdisciplinarity are the use of interdisciplinary core courses and a higher number of faculty directly appointed to the program as well as a dedicated program director. Conversely, weak interdisciplinarity can be found when students can choose from a range of courses that are not intentionally integrated with one another, leaving integration across subjects to the students themselves [152]. However, the impact of these features on student learning is not yet empirically clear [171]. Thus, interdisciplinary curriculum development requires addressing a variety of interrelated issues. Moreover, there is no established consensus on curriculum development approaches or the interplay of organizational features.

3.1.3 Dimensions and Types of Curriculum Change

Curriculum change can be viewed from three dimensions: (1) triggers of change, (2) drivers and barriers of change, and (3) the type and content of change [92, 104, 174].

Triggers of change refer to the impetus of change, from forces within the institution or from external sources [174]. It can be normative or goal-oriented [92].

Drivers and barriers of change can again be differentiated between external or internal influences [104]. Internally, questions about the institutional goals, resource availability, governance structures, and readiness of faculty for integrating and changing [104, 267]. Moreover, student needs and interests as well as their characteristics and abilities might drive or hinder change [104]. Externally, the market forces, the political agenda, accreditation agencies or disciplinary associations, or changes in other institutions might influence the change process [104]. This will be further discussed in Section 3.1.4.

Finally, the type and content of change vary and can be linked to different response strategies, e.g., adding new degrees or course work, new subjects, or integrating aspects in core or electives [104, 158]. From a content perspective, there is the question of what competencies are relevant and categorizing their integration, e.g., in vertical integration (explicit mentioning of competency), horizontal integration (competency implicitly integrated across the curriculum), and a combination of both [169].

Extending the aspects of integrating AI competencies in engineering education, it becomes clear that there is a need to understand how to develop (interdisciplinary) curricula that integrate AI and different engineering domains. This understanding includes questions of what competencies or which content are relevant, and in what sequence it should be taught. In return, changes can lead to adding new competencies, integrating them into existing curricula and courses, or re-building them [158]. More specifically, from a course perspective, there is the need to understand what learners need in their interaction with AI, what relevant instructional resources are, and how these can be structured, assessed, and evaluated.

To date, only a few curriculum and course development efforts on AI in engineering exist in the literature (discussed in detail in Section 3.3). Moreover, as discussed in detail in Section 3.2, the research on understanding relevant AI competencies is still in development. Overall, research focuses on small interventions targeting students, lacking the systematic perspective of change needed along levels of faculty and curriculum development.

Types of Curriculum Changes Related work on change processes and related change efforts toward integrating novel aspects in engineering education exist. Two recent efforts that can inform integrating AI competencies in engineering education are the integration of ethics education and sustainability education in engineering curricula.

For example, Weiss, Barth, and von Wehrden [325] analyzed 131 case studies of curriculum change towards integrating sustainability and identified six implementation patterns ranging from (1) collaborative paradigm change, (2) bottom-up, evolving institutional change, (3) top-down, mandated institutional change, (4) externally driven initiatives, (5) isolated initiatives, and (6) limited institutional change. Similarly, Lambrechts [169] analyzed how and to what extent sustainability-related competencies were integrated into Bachelor programs at their university.

In the context of engineering education, Kolmos, Hadgraft, and Holgaard [158] advanced three different curriculum change strategies: first, an add-on strategy, referring to including additional courses or components in a curriculum but not changing the overall educational paradigm; second, an integration strategy, which involves modifications of programs, and third, a re-build strategy which refers to a fundamental change of the educational paradigms of the curricula. These build up on responses to sustainable education proposed by Sterling [294]: making adjustments in the existing system such as improvements or restructuring and changing the educational paradigm as in redesigning the system and institutions.

To visualize these proposed contextualizations of curriculum change, another helpful example is proposed by Barth and Timm [17], who arrange initiatives in a matrix along their degree of implementation and degree of innovation (see Figure 3.1). This highlights that some curriculum changes are more innovative but also require more implementation effort.

Next to sustainability, engineering ethics is another topic of curriculum change processes in engineering education. In this context, Martin, Conlon, and Bowe [206] analyzed literature through four different analytical levels: individual teaching practices, institutional (programs, departments, implementations), policy (accreditation, funding), and culture (paradigms of practice). This suggests that similar to ethics, AI should be integrated across modules, needs to be put into practice, and is shaped from different disciplinary domains [117].

The applicability of either of these strategies depends on the context as curricular change does not take place in a vacuum and a range of factors shape curricular reform, especially in interdisciplinary efforts [151, 152] and faculty-decision making [172]. Thus, to build a system perspective on integrating AI competencies in

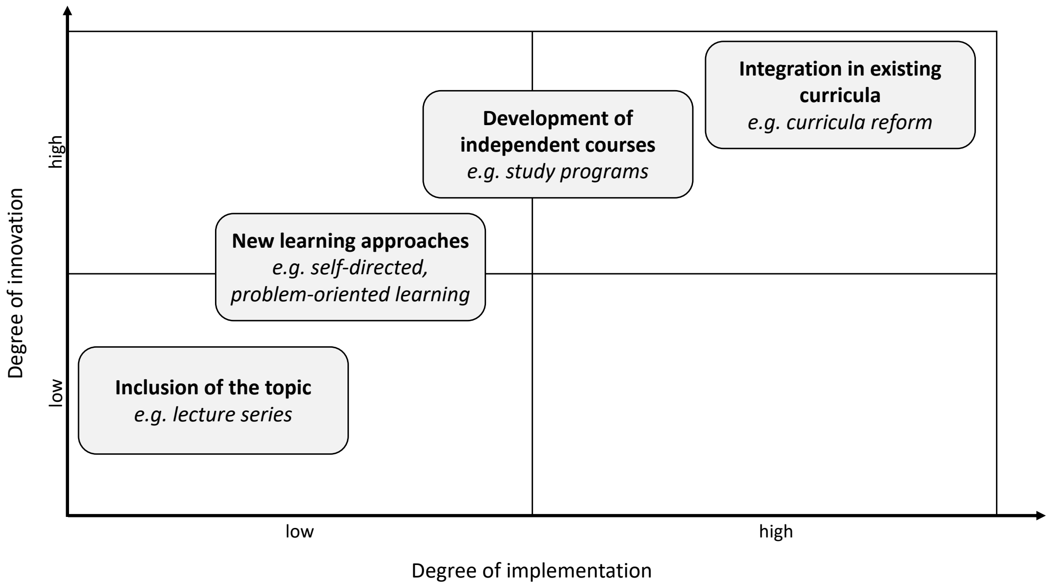

Figure 3.1: Depth of implementation of curriculum change adapted from [17, p. 2].

engineering education, it is important to understand the different influences that shape curricula changes and contextualize them towards AI education.

3.1.4 Influences on Curriculum Change

A theoretical framework that helps to understand the factors that influence design decisions in curriculum and course planning is the *Academic Plan Model* [174]. The model proposes that curriculum and course development, while conducted by faculty, is also influenced by external and internal forces in a socio-cultural context. To move towards a systems perspective on the integration of AI competencies in disciplinary engineering fields, the introduced system view can be extended to highlight external and internal influences [174] as well as individual factors of curriculum decisions [172] (see Figure 3.2). Overall, the system model frames the context that is used to understand and describe how change towards the adoption of AI education might occur.

In the following, the external, internal, and individual level influences are described. Specifically, each perspective is presented and contextualized towards the integration of AI competencies in engineering education, highlighting exemplary questions around the influence factors.

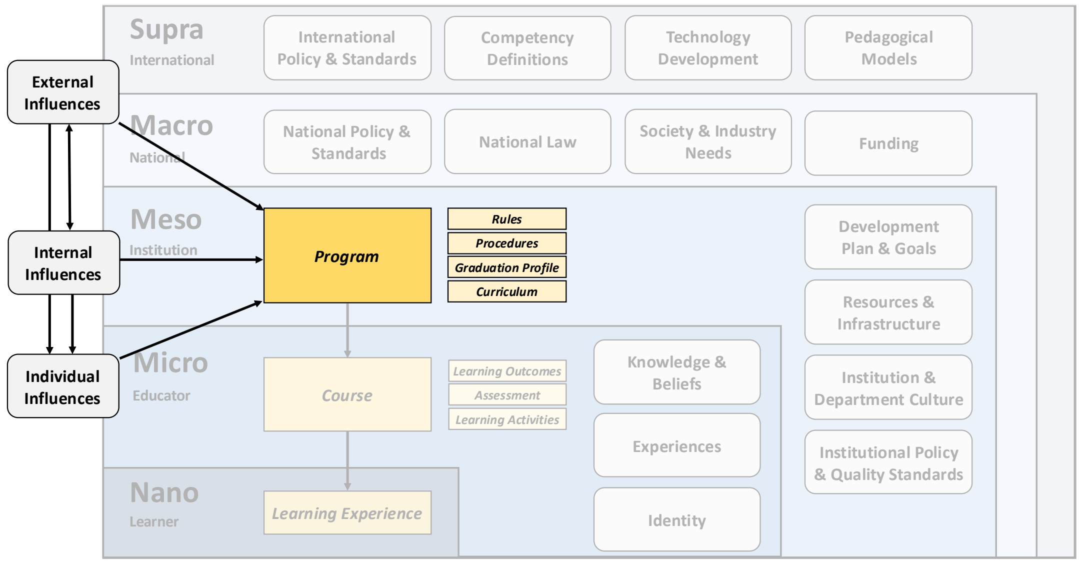

Figure 3.2: Extended systems perspective on influences of curriculum change inspired by [174, p. 4] and [172].

External Influences on Programs and Curricula

The curriculum or academic plan is influenced by internal and external forces [174]. On the external side, Krause [163] highlights three aspects: universal higher education, policy and regulatory frameworks as well as technological changes.

Universal Higher Education The shift towards universal access to university education influences the curriculum through changes in student-staff ratios, changing demographics, and higher diversity of the students in terms of cultures, experiences, and knowledge [163]. This shift also connects to technological changes, for example, allowing larger scale online delivery of courses (e.g., Massive Open Online Courses (MOOC)) that widen the audience and influence curricular concepts.

Policy and Regulatory Frameworks Another external force shaping the curricula is policy on national and international levels as well as economic and labor market forces [163]. An example is expectations from the industry for skills and competencies towards employability [24]. Moreover, higher education institutions are accountable to the government and their regulations.

Technological Changes Technology in itself influences curricula by allowing other forms of education, curricular composition, and delivery. One example is the direction of micro-credentials which allow certification of smaller milestones or skills achieved [211]. Combined with the online delivery of courses and the advantage of high flexibility, these offer other forms of targeted development and also challenge higher education's role of granting and certifying qualifications [211]. Similarly, AI technology influences curriculum from advancing novel delivery methods and assessments to changes in content [31, 188].

Given the different external forces, Krause [163] concludes that there is "need for focused efforts to develop curriculum philosophy and scholarship to allow for an informed approach to defining, designing and evaluating curriculum in its broadest sense, beyond the simple focus of a 'course'" [163, p. 47], especially towards the conceptual frames and rigorous evaluation of outcomes of curriculum changes.

Towards Integrating AI Competencies in Engineering Education The mentioned theoretical factors can also be contextualized in the change towards AI education. First, the development of AI has accelerated in recent years, mainly due to technological advances in computing and model architectures. In addition, industry AI research is gaining significance over academia [2]. This leads to new market forces and industry demand for AI talent, and as a result, demand for more AI education across all disciplines. Second, the need for AI talent and research is also picked up by governments and supported through funding or political initiatives [88], which create an opportunity for universities to develop new programs or research initiatives. Third, new competencies are also taken up by accrediting bodies. However, a recent article highlighted that currently AI is not yet broadly integrated into engineering accreditation [305]. Fourth, the use of AI systems has ethical, legal, and social implications, and is also a topic of regulatory aspects [263]. Regulations such as the EU AI Act [263] influence the possible use of AI systems but in a broader sense also what should be taught in the context of AI education for responsible engineers. Fifth, there exists the challenge of a high volatility of skills because of technological advancements [93, 215, 340]. Identifying the relevant competencies and adopting courses and curricula at the required speed remains challenging for higher education.

Exemplary Questions To this end, some exemplary questions for curricular change to consider in context of the external influences are:

- How important is AI on the current political agenda?
- What is the demand for AI skills in the industry? Who are potential partners?
- How much funding is available to develop new programs?
- How is the technological change in AI affecting the relevant competencies and their adoption in programs and courses?

Internal Influences on Programs and Curricula

Concerning internal influences, Lattuca and Stark [174] distinguish between institutional such as the objectives of the institution, resources or governance, and unit-level influences such as educators in faculty, discipline culture, and student characteristics. Thus, internal influences are closely related to organizational theories for institutional change [34]. In this context, Scott [279] highlights three central pillars that influence change in an institution: the rules, the norms, and the cultural-cognitive beliefs [279, p. 49]. The *regulative* pillar focuses on how "institutions constrain and regularize behavior" [279, p. 52], thus setting rules, monitoring them, and putting measures in place if rules are not obeyed to. In the context of higher education, regulative action might come from quality standards, approval of courses or programs, and university council decisions. The *normative* pillar addresses the values of an institution and its norms, thus focusing on how things should be done. Last, the *cultural-cognitive* pillar refers to the shared beliefs, internalized values, and routines in an organization [279, p. 57]. In summary, understanding these perspectives provides a base of influence and steering in organizations.

Institutions show an inertia against the change of content in practices [111, 138, 210], which can be argued with the theoretical concept of path dependency [164]. As universities function as institutions, the discourse surrounding education often reflects a conservative stance [138] and established practices tend to be institutionalized and reinforced. Moreover, institutions operate in a system where they have to adhere to external standards as well as are dependent on actors on a national level, e.g., through funding or national law. Additionally, in terms of content changes Jónasson [138] argues that "the fact that one may seriously threaten a variety of vested interests and ideals of those who are already lodged in the system, presents a vast challenge for those who argue for replacing the old with the new" [138, p. 7]. This addresses, for example, the resistance of educators who might be faced with the insecurity of giving up their subject, reinventing their role, or even losing their jobs [138].

Towards Integrating AI Competencies in Engineering Education Overall, the internal influences demonstrate the organizational complexity when integrating AI education in engineering education. One key challenge is the readiness of faculty for change, be it the level of expertise and skills in AI, the needed support structures, or the potential resistance to change [292]. Moreover, aspects such as governance structures are important to consider. For example, Knight et al. [152] highlighted the importance of organizational features, such as the appointment of a program director and faculty appointment within the interdisciplinary field. Additionally, in the context of AI, computational resources are needed for deployment, experiments, and teaching. Thus, it is important to consider what resources are available on a faculty and institutional level.

Exemplary Questions From within the organization, some exemplary questions for curricular change to consider are:

- Who is driving the integration of AI education? Is it led by leadership (top-down) or by faculty/educators/students (bottom-up)?
- How well embedded is AI education in the faculty goals or strategic initiatives?
- How well-equipped are educators to teach AI topics?
- What governance structures can support the integration of AI in curricula?
- How is the funding and resource situation, e.g., for computing at the institution?

Individual Influences on Programs and Curricula

Faculty and educators are at the core of implementing and acting on these influences. Thus, it is important to consider how the decision-making of faculty on curriculum changes on a program and course level are influenced.

In this context, Lattuca and Polland [172] proposed a model conceptualizing faculty decision-making in curriculum changes, illustrated in Figure 3.3. The model highlights how individual decision-making is influenced by both external and internal influences, such as institutional policies, disciplinary norms, and university governance structures, as described before. However, it also underscores the importance of individual-level factors, including competencies, beliefs, past experiences, and professional identity. Research on innovation in higher education indicates that while external and internal factors are well-studied, the role of individuals as innovators remains underexplored [111], partly because of the assumption that the agency of faculty in a highly institutionalized context of higher education is often constrained by administrative structures, resource limitations, and broader societal expectations.

Towards Integrating AI Competencies in Engineering Education These factors can also be contextualized in integrating AI competencies in engineering education. For example, educators' beliefs about the relevance and role of AI in engineering can influence their openness to curricular change. Research indicates that the personal factors of educators, such as their beliefs about education or their view of their own

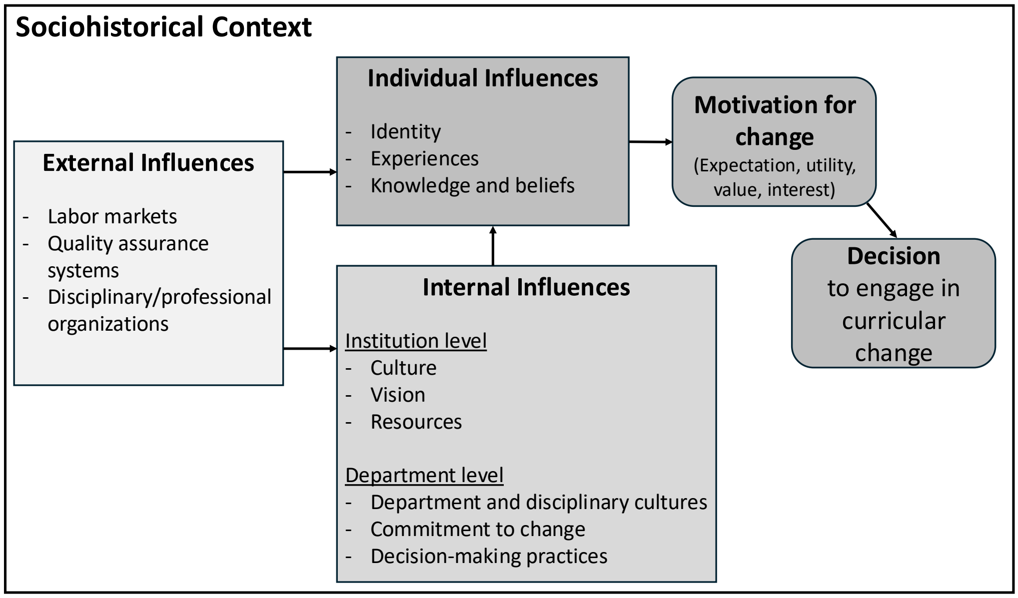

Figure 3.3: Influences on faculty-decision making in curricular changes (adapted from [172, p. 103]).

discipline, strongly influence curricular choices [172, 292]. Especially faculty who identify strongly with traditional engineering disciplines might struggle to incorporate AI topics into their courses. Thus, if educators are part of the curriculum development of programs, their strong beliefs about their own discipline make interdisciplinary curriculum developments more challenging. This also highlights the need for communicative approaches in curriculum development and change that allow for deliberations (cf. Section 2.2). At the same time, it is still unclear how the participation of educators allows changing their views and assessment of quality.

Another aspect is the potential lack of expertise in AI and the need for additional professional development to teach AI-related content [235]. Last, the workload and perceived misalignment with promotion and tenure incentives might hinder the engagement with curriculum change.

Exemplary Questions On the individual level, some exemplary questions for curricular change to consider are:

- What is the readiness of faculty in terms of AI-related competencies and teaching about AI?
- What beliefs or attitudes among faculty might act as barriers to integrating AI competencies, and how can these be addressed?

- What is the perception of the role of educators in integrating AI competencies?
- What AI competencies are targeted and should be integrated?
- What learning activities and assessment strategies are suitable for AI education?
- What incentives are needed to stimulate change?

3.1.5 Challenges of Integrating AI Competencies in Engineering Education

The introduced systems perspective on the current state of AI education integration in engineering disciplines allows for a first understanding of the change processes required to integrate AI competencies. On the one hand, this can serve as a reference for educators and faculty leaders to see where they stand and how to develop a change strategy for integrating AI into their educational offerings. On the other hand, it also helps to identify current challenges and position the contributions of this dissertation in the context of the emerging field of domain-specific AI education in engineering.

Conceptualization Challenge: Understanding Required AI Competencies One challenge is to formalize and understand the required competencies that shape engineers' work with AI. Thus, in the context of engineering education, understanding what to teach (discussed in Chapter 4). The conceptualization of AI competencies for all is still evolving [8, 177, 255], and the particular view for different user groups, such as an engineering-specific view of competencies, needs to be defined [255]. This conceptualization may include understanding how engineers work with AI in current practice and what competencies become relevant at the intersection of AI and engineering.

Operationalization Challenge: Developing Interdisciplinary Curricula for AI The operationalization challenge arises from the difficulty for institutions to respond to new competencies and build programs around them [138]. To date, there is no systematic understanding and evidence on education about AI [233]. As pointed out, there has been curriculum change research regarding sustainability [169, 325] or the integration of ethics education [117] in engineering education. However, interdisciplinary curriculum development in engineering in the context of AI has not yet been addressed. Thus, there is a need to understand how to develop program structures of AI education in particular in the context of engineering education (discussed in Chapter 5).

Empowerment Challenge: Enabling Educators to Teach About It Third, faculty and educators play an important role in the change process [172]. Thus, another challenge is to train and empower educators to develop domain-specific AI courses and to support them in reflecting on the necessary curricular changes. Educators need guidance on how to frame and reflect on AI competencies in the context of their domains (discussed in Chapter 6).

Benchmarking Challenge: Understanding Initiatives and Interventions Building a foundation for transferring local best practices to more general contexts and supporting the emergence of the interdisciplinary field of AI and engineering requires developing evidence with a nuanced view of change initiatives in local contexts. This should involve collecting and analyzing more case studies, for example through the analytical lens provided above or at lower levels such as learning methodologies [255]. This could be further enhanced with metrics, such as a readiness scale, to support change processes in universities and allow for comparisons at faculty, institutional, national, or international levels. In addition, the internal and external drivers of AI education can benefit from more research, particularly to map change theories to the drivers [264] or to integrate theoretical aspects of technology adoption in education [189].

Effects Challenge: Measuring the Impact of AI Competencies on Engineering Practice Overall, the area of studying the effects of AI competencies in relation to other constructs has been underexplored [255]. This is related to the challenge of conceptualizing AI competencies and the difficulty of isolating effects of AI competencies related to other effects.

The following sections elaborate on these challenges, focusing in particular on the current state of the art in the context of AI competencies (Section 3.2), operationalizing AI competencies (Section 3.3), and supporting educators (Section 3.4), aligned with the addressed empirical contributions of this dissertation.

3.2 Conceptualizing AI Competencies

Competencies are at the center of many educational interventions (cf. Section 2.1). In order to keep educational programs and courses relevant, there is a need and a desire to anticipate changes in competencies, for example because of new demands from employers and changes in technology [90, 249, 335].

The following section first provides an overview of the discourse on AI and related competencies before introducing different types or views of AI competencies. Furthermore, assessment methods for AI competencies are introduced in Section 3.2.6. The section builds in part on the papers [pub:6] written with Maria Klar, [pub:2] written with Marie Decker and others, and [pub:25] written with Katharina Schueller, Florian Rampelt, and Henning Koch. Overall, the section aims to provide an overview of current work on conceptualizing AI competencies, particularly for engineers.

3.2.1 Discourse on AI and related Competencies

Widely available (generative) AI tools and technologies are fueling the discourse on the required AI competencies. Questions arise as to whether new competencies are needed in dealing with AI (often referred to as AI competencies), whether other skills are becoming less important, and whether a process of unlearning is taking place. In the face of uncertainties, there is a desire for orientation, for example in the formulation of *future skills* or often called *21st-century skills* (e.g., [80]). However, it is questionable to what extent this promise of being able to prepare for an uncertain future can be kept [82].

Views on AI Competencies A key question is whether AI competencies are independent, stand-alone competencies or whether they permeate existing competencies. Many papers refer to a concept of *digital competencies*, with the implication that this is a separate set of additive skills. However, Kerres [147] argues that digital technologies permeate existing cultural techniques and that separate teaching and learning of digital competencies is not meaningful. The interconnections are also highlighted in an effort to provide a model for digital education in Germany, the so-called *Dagstuhl Triangle* [40, 41]. It highlights three perspectives on digital education, a structural perspective (structure and functioning of systems), an application-oriented perspective (i.e., what tools for what purpose), and a socio-cultural perspective (i.e., interaction between system, individual, and society).

An attempt to define AI competencies is being made through the discourse on *data and AI literacy* [8, 191, 234, pub:25]. This is also promoted by more recent frameworks from international bodies such as the United Nations Educational, Scientific and Cultural Organization (UNESCO) [310, 311], or the EU with the Digital Competence Framework for Citizens (DigComp) [137]. The central assumption of these efforts is that new competencies are needed in dealing with data and AI systems. Thus, AI competencies in this context are to be interpreted as dealing with AI systems and technologies. One example is the ability to effectively formulate prompts and develop strategies for working with generative tools and instruments [35, 36]. This is comparable to search literacy, which emerged with the advent of the internet and is often listed as a dimension of information literacy [179].

Generative LLMs and corresponding tools are also changing the way knowledge is accessed. First, non-representative studies on the use of generative AI at German universities show that 63% of students already use generative models in their studies and that the main areas of application are the clarification of (subject-)specific questions, research and literature work, translations as well as problem-solving and decision-making [317]. The question remains, however, to what extent AI technology will lead to entirely new knowledge practices from which new skills can be derived, or whether existing practices will be extended to include aspects of these technologies.

Connection to Other Competencies Kalz [140] highlights a number of problem areas regarding the formulation of *future skills* that are also relevant to the discussion of AI competencies. He argues that there needs to be a link to previous competency models instead of creating new lists of (AI) competencies, the selection and prioritization of which needs to be newly justified [140]. Furthermore, the measurement of such competencies is a challenge and empirical research on the effects of increasing AI competencies in performance situations is needed [140]. These aspects are also highlighted in a critical review of AI competency frameworks for teachers [216]. As with digital literacy, the question arises whether AI literacy is actually a plurality of skills that can only be taught and learned if they are anchored in the subject [146].

In summary, there is a problem of terminology. AI competencies include existing competencies and are not fundamentally new. However, the way in which data and AI are used leads to new knowledge practices and increases the importance of a fundamental understanding of how AI algorithms and data work. In addition, current practices in the disciplines are changing toward more data-driven approaches and practices, requiring changes in curricula and courses [255].

Uncertainties of Relevance Even if it would be possible to formulate AI competencies that would remain valid in the future, uncertainties remain. The reality that AI-based tools can do certain things faster and more reliably than humans changes the meaning and importance of these competencies. For example, it can take years to decipher how a single protein folds. An AI model called *AlphaFold* has now solved this for most proteins in a fraction of the time [139].

In the context of competencies and education, it must therefore be questioned how we deal with the situation that competencies that we possess or are currently learning may become irrelevant because of technical automation. In addition, the social and societal dimensions, such as the loss of status or the feeling of humiliation when human work performance is no longer competitive, should be addressed. Continuous upskilling or reskilling could be made more difficult by dynamic technological development [109], especially as it is difficult to predict which activities can be performed by machines in the near future.

Deskilling Effect There is also the challenge of unlearning skills, also known as *deskilling*. By using increasingly powerful tools, such as AI, people are transferring responsibility to them and may be less able to perform basic skills [245, 260, 265]. One explanation is provided by research on cognitive offloading, which shows that temporary offloading to technological tools leads to better performance in the short term, but worse retention in the long term [103]. Hamilton et al. [109] even speak of *de-education*, the loss of education because of the situation that people are no longer motivated to acquire skills in the face of superhuman AI. The potential loss of skills is also seen as a risk by students [101]. The outsourcing of processes to (digital) technologies is not a new trend in itself and is an everyday practice, for example in the use of automatic spelling correction or the use of a calculator. A central question here is whether the basic skills of the tools must first be mastered before they can be used, as is discussed in mathematics didactics under the term reverse scaffolding [53]. Above all, basic skills should lead to critical and reflective use and a reduction of dependence on digital technology [265].

In this context, overestimating one's own abilities in the field of AI is also problematic. As has been shown in various fields, people with little prior knowledge tend to overestimate their own abilities [77]. This can also be observed in the context of AI and related skills, and can lead to an overestimation of one's own abilities combined with an underestimation of the risks [112].

In the view of these discussions, it can be concluded that the acceleration of technological development leads to a change and altered weighting of skills. On the one hand, there are (subject-specific) competencies in dealing with AI systems. On the other hand, there is a change in the importance of human skills such as critical thinking, empathy, or imagination as opposed to machine skills such as processing and evaluating large amounts of data. This shift and rebalancing should also lead to a discussion of the impact of technological developments on examination formats and the methodology of educational programs.

Types of AI Competencies To develop a holistic understanding of AI competencies, the following section introduces different types of AI competencies following the distinction proposed in our paper [pub:19] and further extended by Knoth et al. [153]. This distinction includes (1) *generic AI literacy*, which is the broad understanding of AI, (2) *domain-specific AI competencies*, which are the discipline-specific competencies for working with AI in the context of a domain, (3) *expert AI competencies*, and (4) *ethics-related AI competencies*, which refer to ethical components of AI competencies. Table 3.1 provides an overview. Note that these types are not mutually exclusive, but are intended to provide structure to a complex and broad field. The distinction aims to highlight the interplay of general literacy and disciplinary depth as well as different maturity levels. Further discussion can be found in recent systematic reviews [8, 177, 255].

Table 3.1: Types of AI competencies with respective descriptions, systematic reviews, and example frameworks.

Type	Description	Systematic Reviews	Example Frameworks by Target Group
Generic AI literacy competencies	Foundational knowledge, skills, and attitudes to engage with AI in everyday life	[51, 177, 234, 338]	Society [137, 141, 191, pub:25], K-12 [303, 304, 310], Workforce development [11, 338]
Domain-specific AI competencies	Knowledge, skills, and attitudes related to AI tailored to a particular field or specific context	[51, 255]	Business education [341], Teacher education [313], Professional education [270], Non-CS students [297], Technology education [295], Medical education [47]
Expert AI competencies	Advanced competencies to design, develop and implement AI systems	-	Experts [96, 220, 269, 337]
Ethics-related AI competencies	Competencies around ethical implications of AI systems and personal role	-	Various [73, 153]

3.2.2 Generic AI Literacy Competencies

The term AI literacy was first introduced in 2016 by Kandlhofer et al. [141] as AI competencies for society, but was popularized through the paper by Long and Magerko [191] in 2020. Their initial definition conceptualizes AI literacy as "a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace" [191, p. 2]. This also positions the core of generic AI literacy as competencies of the general public, thus as competencies that every educated citizen should possess, similar to other literacy concepts such as reading literacy or information literacy.

Frameworks Given the widespread relevance, it is clear that several researchers and policy organizations have taken up the concept and created their own interpretations or frameworks of it [8, 177]. In Europe, a recent update of the EU's *DigComp* framework [137] includes the topic of citizen interaction with AI systems. The framework outlines digital competencies in several areas, including information and data literacy, communication and collaboration, digital content creation, safety, and problem solving. Specifically for AI systems, it details the necessary knowledge, skills and attitudes. These include understanding what AI systems can and cannot do, recognizing their benefits, limitations, and associated challenges, and being able to use, engage with, and provide feedback on these systems as end users [137, p. 77]. It also covers skills for configuring, monitoring and adapting AI systems [137, p. 77]. The framework also emphasizes attitudes such as human agency and control, maintaining a critical yet open mindset, and addressing ethical considerations [137, p. 77].

Similarly, Schueller et al. [pub:25] describe a framework that informs the development of an Institute of Electrical and Electronics Engineers (IEEE) *Standard on Data and Artificial Intelligence Literacy, Skills, and Readiness* [url:8]. The proposed framework promotes the use of roles in conjunction with competencies, following other researchers [87, 329]. In this context, the framework defines three main roles: (1) an informed prosumer who produces and consumes data in an informed manner, (2) a skilled user who uses data and AI in a responsible and skilled manner, including application-relevant skills that go beyond consumption and sharing, and (3) an expert creator who creates new insights, solutions, and tools with and based on data and AI [pub:25, p. 429].

In September 2024, the UNESCO also proposed a *Competency Framework for AI Competencies for Students* [310], which aims to provide an international reference framework. In the framework, competencies are structured along four aspects of human-centered mindset, ethics of AI, AI techniques and applications, and AI system design. It also proposes three progression levels of understanding, applying, and creating, leading to twelve blocks of competencies that students should address. The framework is aimed at schools and is accompanied by a corresponding framework of AI competencies for teachers [311].

Overall, with the multitude of conceptualizations and frameworks available, recent systematic reviews highlight that there seems to be no consensus yet on what generic AI literacy entails [8, 177].

Target Groups In addition to the general population, there are a number of initiatives that focus on different target groups, namely students in primary and secondary education [50, 180, 303, 304, 339, 346], higher education [177] and workforce development [11, 338].

Competency Areas Generic AI literacy can be positioned as context-independent competencies needed to operate and act in an AI-driven world [153, 191]. Recent systematic reviews show that the conceptualization of what competencies constitute AI literacy varies [8, 177]. In systematic reviews, a common structure refers to *different cognitive levels of objectives* (e.g., the Bloom's taxonomy [27, 162]). For example, Ng et al. analyzed research highlighted four constructs of *know and understand AI*, *use and apply AI*, *evaluate and create AI*, and *AI ethics* [234, p. 4], following Bloom's taxonomy. Accordingly, a recent systematic review, Almatrafi, Johri, and Lee [8] provided an overview of existing frameworks along the dimensions of *recognize (be aware)*, *know and understand*, *use and apply AI*, *evaluate*, *create* and *navigate ethically*.

Other authors argue for a clear *differentiation of knowledge, skills, and attitudes* [153]. For example, Lao [170] focuses on *knowledge aspects* (i.e., general Machine Learning (ML) knowledge, knowledge of ML methods, bias in ML systems, and societal implications), *skills* (i.e., ML problem scoping, ML project planning, creating ML artifacts, analyzing ML design interactions and results, ML advocacy, independent out-of-class learning), and *attitudes* (interest, identity, self-efficacy, persistence). Similarly, Kong and Zhang [160] proposed a framework along the *cognitive*, *affective*, and *sociocultural* dimensions, where the *cognitive dimension* focuses on understanding basic AI concepts and skills, the *affective* on empowering individuals to collaborate effectively with AI, and the *sociocultural* on promoting the ethical use of AI.

Another way to structure competencies is to *group them together under themes*. For example, Casal-Otero et al. [50] point to *learning about AI*, *learning about how AI works*, and *learning for a life with AI*. Similarly, Long and Magerko [191] proposed 17 competencies in five groups of *What is AI?* (Recognizing AI, Understanding Intelligence, Interdisciplinarity, and General vs. Narrow AI), *What can AI do?* (AI strengths & weaknesses and imagining future AI), *How does AI work?* (Representations, Decision Making,ML steps, the human role in AI, data literacy, learning from data, critical interpretation of data, action and reaction, and sensors), *How should AI be used?* (ethics), and *How do people perceive AI?* (Programmability). Similar structures are used by the AI4K12 five big ideas for AI [303, 304] and the DigComp framework [137].

Other frameworks, such as the recently proposed UNESCO frameworks [310] or the currently developed IEEE standard on data and AI literacy [url:8] are *hybrids*, thus using both competency domains as well as progressions or distinctions of knowledge, skills, and attitudes.

In summary, generic AI literacy and related competencies remain a dynamic field that can be structured by different perspectives. Furthermore, recent literature reviews indicate that there is currently no clear consensus on what AI literacy entails [8, 177].

3.2.3 Domain-specific AI Competencies

Next to competencies that aim at a broad understanding, domain-specific AI competencies aim at the application of AI within the context of a professional domain or specific usage context [153, 255, pub:19]. In this context, domain refers to a discipline or specific field in which AI is implemented or used in practice. Thus, rather than aiming at a broad target group, it is targeted towards certain user groups [255]. Knoth et al. [153] emphasize that "domain-specific AI literacy is underexplored in current research, but important insights could be gained from the literature dealing with the design of AI education" (p. 4). According to this argument, domain-specific AI competencies "might refer to the capacity to integrate the knowledge of AI with the comprehension of its application requirements within a particular professional field" [153, p. 4]. This reflects views and the development of expertise and is also linked to the desire to define sub-competencies for different roles. At its core, it recognizes that relevant AI competencies vary by application case and domain. However, recent studies indicate that students outside of computer science feel inadequately prepared for the growing presence of AI in their disciplines [256, 285].

Frameworks Domain-specific AI competencies can be found in discipline-specific AI education. Examples include business education [341], teacher education [313], medical education [47], technology education [295], and in professional education [270].

Competency Areas In their review of AI literacy for workplaces, Cetindamar et al. [51] propose four areas of competency for AI, (1) *technology-related*, (2) *work-related*, (3) *learning-related*, and (4) *human-machine-related*. Similarly, in their systematic review of AI literacy for users, Pinski et al. [255] point to proficiency dimensions and subject areas [255, Figure 4 and 5]. In the *proficiency dimensions*, they distinguish between knowledge, awareness, skills, competencies, and experience, while the *domain areas* are structured along AI models, data for AI, AI interfaces, AI tools, humans, organizations, and society, as well as cross domain. Following our work [pub:19], Knoth et al. [153] propose that domain-specific AI literacy should target aspects of *potential AI use cases* in the domain, the *data* in the domain, and *implications* of using AI in the domain. Similarly, in an interview-based study on AI competencies for non-CS undergraduate students, Tenório and Romeike [297] advance a list of competencies along areas of computing, basics of AI, AI capabilities, multidisciplinary AI, data, machine learning, advanced machine learning, human-AI interaction, responsible AI and others.

3.2.4 Expert AI Competencies

Expert AI education focuses on the competencies needed to advance AI methods and conduct AI research. It is often found in the context of advanced education in computer science, data science, or related disciplines, as well as in industry contexts. Thus, expert AI competencies aim for a higher maturity and are often focused on a particular methodology or domain.

Framework Examples include advanced graduate or postgraduate AI courses, research seminars, or industry training. While these are not competency frameworks, established textbooks such as Russell and Norvig's *Artificial Intelligence: A Modern Approach* [269] and Goodfellow et al.'s *Deep Learning* [96] are often adopted as syllabi to provide a structured approach to understanding AI systems and their applications. Similarly, the *AI Skills for Business Framework* [299] highlights the role of AI professionals with core responsibilities in AI and data, and the role of AI leaders responsible for AI governance and procurement.

Competency Areas AI professional competencies aim to develop a deep understanding of the theoretical foundations, modeling techniques, model architectures, current limitations in the field, and possible advancements in methods [337]. For example, the *AI Skills for Business Framework* [299] outlines five key dimensions of AI skills for professionals:

- *Privacy and Stewardship*, emphasizing the security and protection of data throughout its lifecycle, while complying with legal, regulatory, and ethical considerations.

- *Specification, Acquisition, Engineering, Architecture, Storage, and Curation*, which focuses on the collection, secure storage, manipulation, and curation of data, as well as competencies in data management and the handling of sensitive information.
- *Problem Definition and Communication*, relating to the ability to identify and clearly define problems, understand the role of artificial intelligence in potential solutions, and communicate effectively to diverse audiences.
- *Problem Solving, Analysis, Modeling, and Visualization*, which emphasizes the use of mathematical, statistical, and computational tools to define and analyze problems and present solutions.
- *Evaluation and Reflection* emphasizing the importance of ethical understanding and responsibility in ensuring the integrity of models developed in the field.

In Russell and Norvig's textbook [269], which is used as a syllabus for many advanced AI courses, they cover areas such as (1) *Introduction to AI*, (2) *Problem Solving*, (3) *Knowledge, Reasoning, and Planning*, (4) *Uncertain Knowledge and Reasoning*, (5) *Machine Learning*, (6) *Communication, Perception, and Action*, and (7) *Conclusions on the Philosophy, Ethics, and Safety of AI*. Similarly, in their book on deep learning, Goodfellow et al. [96] emphasize the importance of building strong mathematical foundations. The book focuses on topics such as applied mathematics, machine learning foundations, modern practical deep networks, and deep learning research. These areas are essential for developing a deep understanding of the theoretical underpinnings and latest advances in AI. In addition to theoretical knowledge, expert AI education also places a strong emphasis on developing practical skills (e.g., programming, setting up experiments, research, problem solving) as well as promoting the interdisciplinary nature of AI by incorporating concepts and methods from fields such as mathematics, philosophy, cognitive science, neuroscience, and psychology [220].

3.2.5 Ethics-related AI Competencies

Ethics, or the ethical or responsible use of AI, is recognized in several AI competency frameworks, sometimes implicitly and sometimes explicitly [8, pub:2, 153]. Recognizing that AI systems are embedded in socio-technical systems, we can refer to the notion of *responsible AI* or *ethical AI* as "the fact that decisions and actions taken by intelligent autonomous systems have consequences that can be seen as being of an ethical nature" [73, p. 48]. Persons involved in the development, deployment, and use of AI need to consider the ethical, legal, and social implications of the use of the technology, which requires certain ethical reasoning, making it important to consider the related competencies [258]. Thus, in order to put the responsible development and use of AI into practice, guidelines point to the importance of considering both technical and societal perspectives [108, 258], arguing for the explicit formulation of ethics-related AI competencies [153].

Frameworks Only through additional awareness of individual and structural barriers can responsibility be undertaken [73]. The aspect of ethics can often be found integrated into generic AI literacy frameworks aimed at the broad audience of AI users [8, 153, 310]. However, some frameworks explicitly address responsibility [pub:2, 297]. While the ethical use of tools can be attributed as a general AI competency or to the particular users of the system, the responsibility for AI systems is primarily attributed to engineers and the stakeholders associated with their efforts [76]. In the engineering context, many engineering competency frameworks, accreditation standards, and curricula already emphasize responsible behavior for engineers [203]. In collaborative work on this topic, we conducted an exploratory literature review on responsible AI competencies for engineers [pub:2]. We found that while most frameworks include ethical components, they often lack the necessary nuance and detail in discussing ethics-related AI competencies [pub:2].

Competency Areas In AI competencies, ethics is often mentioned in the context of critical evaluation and ethical navigation [8, 234]. Moreover, critical evaluation seems to include classic aspects of professional responsibility [297] and is thus closely related to other, more diversified ethical constructs. Tenério and Romeike [297] explicitly advanced competencies for responsible AI on different proficiencies (i.e., describing AI-related ethical issues, discussing the consequences and dangers of ethical concerns of AI, assessing possible positive and negative effects and impacts, or applying procedures that can mitigate ethical problems).

A more nuanced view is proposed by Hess and Fore [116] in a review of engineering ethics interventions, which can also be applied to the analysis of competency frameworks at the intersection of AI and engineering. The first aspect is *ethical sensitivity or awareness*, as in increasing students' recognition of ethically problematic situations and sensitivity to ethical issues they may face [116]. Across our analysis [pub:2], all frameworks included this awareness of ethical issues, for example, by mentioning knowledge of the ethical principles of fairness, accountability, and transparency [30], or identifying more general opportunities and risks posed by AI [191]. Second, *ethical* *judgment, decision-making, or imagination* refers to acting ethically and reasoning about ethics, for example, by understanding and discussing ethical theory or codes of ethics, or by applying technical knowledge responsibly. An example is the competency mentioned in the responsible AI competencies by Tenório and Romeike [297, p. 9] as “Apply procedures when developing AI tools that can mitigate ethical problems”. Third, *developing ethical courage, confidence, or commitment* targets underlying attitudes and values by aiming to develop a commitment to ethical principles or a motivation to act ethically [116]. This perspective is least addressed in AI-related competency frameworks [pub:2].

In summary, the analysis highlights the ongoing debate among educators and competency framework authors as to whether ethical competencies in AI should be considered as an integral part of broader competencies or as a distinct category [153, 234]. While treating these competencies separately allows for focused consideration, it overlooks the complex nature of responsibility competencies [116]. Overall, there is a clear need to cultivate practical ethical behavior and a robust ethical disposition in students learning about AI. The competencies required for this do not appear to be well defined yet [pub:2].

3.2.6 Assessment of AI Competencies

The definition of competencies often accompanies the development of assessment tools [177, 187]. These provide a basis for understanding and comparing the implementation or interventions in AI curricula and courses.

As the different dimensions of AI competencies have only recently been widely discussed and researched, the available assessment instruments are also only limited. Table 3.2 provides an exemplary overview of various assessment instruments that have been developed in recent years focusing on *Self-assessment (SA) tools*, *tests*, and *scales measuring Attitudes towards AI (ATAI)*.

These assessment instruments provide a starting point for further systematization and comparison of interventions [187]. In addition, they provide insight into conceptualized areas of competencies. At the same time, the approaches and scales need to be further tested in practice to see their usefulness and validity as well as further contextualized to address not only generic AI competencies but a holistic view [153].

Table 3.2: Exemplar validated AI literacy assessment approaches along categories of Self-assessment (SA), tests, and Attitudes towards AI (ATAI).

Tool	Type	Competency Areas	Description
Wang et al. [320]	SA	Awareness, Usage, Evaluation, Ethics	12 items with Likert scales, validated with exploratory and confirmatory factor analysis
Carolus et al. [49]	SA	Use and apply AI, Understand AI, Detect AI, AI ethics	34 items with Likert scale, validated with confirmatory factor analysis
Pinski & Benlian [254]	SA	AI technology knowledge, Human actors in AI knowledge, AI steps Knowledge, AI usage experience, AI design experience	13 items, targeting workforce development
Laupichler et al. [176]	SA	Technical understanding, critical appraisal, practical application	31 items developed through Delphi method and validation with EFA and CFA
Ng et al. [237]	SA	Affective, behavioral, cognitive, ethical	32 items targeting secondary students, validated with EFA and CFA
Jang et al. [132]	SA	Ethical dimensions of fairness, transparency, non-maleficence, privacy, and responsibility	17 items measuring adherence to ethical dimensions
Shih et al. [280]	SA	Ethical principles of transparency, responsibility, justice, benefit	15 items to measure effects of AI ethics course
Chiu et al. [58]	SA	Teachers self-efficacy on AI knowledge, AI pedagogy, AI assessments, AI ethics, human-centered education, and professional engagement	24 items on six dimensions, developed with Delphi study, validated with confirmatory factor analysis and model comparisons
Delcker et al. [71]	SA	Theoretical Knowledge about AI, Legal Framework and Ethics, Implications of AI, Attitude toward AI, Teaching, and Learning with AI, Ongoing Professionalization	45 items along six categories targeting teachers validation with CFA
Wang & Chuang [322]	SA	Individual's perceived self-efficacy regarding the use of AI technologies/products	22 items validated with EFA and CFA
Tully et al. [306]	Test	NA	25 items testing AI literacy of individuals
Weber et al. [323]	Test	Socio- and Technical AI literacy, user and creator/evaluator	16 items testing individuals AI literacy
Hornberger et al. [121]	Test	Competency areas of [191]	31 items testing individuals AI literacy with multiple choice and sorting validated with CFA and IRT
Chiu et al. [59]	Test	Dimensions of knowledge of AI, process in AI and impact of AI	25 multiple choice items tested with school children grade 7-9
Schepman & Rodway [274]	ATAI	Positive and negative attitudes towards AI	20 items that ask for positive and negative attitudes, validation with CFA
Sindermann et al. [283]	ATAI	Attitude towards AI on acceptance and fear dimension	5 items, validated through PCA and CFA

3.2.7 Challenges

In summary, the state of the art has revealed certain challenges when it comes to AI competencies in general and engineering education in specific.

Broad and dynamic range of AI Competencies Currently, there is no clear consensus on what constitutes AI literacy or competencies around AI [8, 177, 255]. Moreover, new functionalities of AI, especially in the context of generative AI, change the relevant competencies in roles to some extent. From a practical perspective, this makes it challenging to develop targeted educational offerings and interventions. At the same time, it also highlights the need for further research, especially in the underexplored area of domain-specific AI competencies that are anchored in a particular domain [153, 255].

Assessment Currently, most assessment instruments (cf. Table 3.2) target generic AI literacy competencies as well as attitudes or ethical components. While this is a good starting point to build on, there is a need to develop more holistic and domain-specific measures that incorporate the specific context and requirements of professional domains and applications [8, 153]. In addition, further validations and comparisons of the scales, similar to [155], are needed to establish validity. Finally, an operationalization of how these tests can be effectively used in interventions targeting AI competencies needs to be further established. A starting point could be the collaboration with Matthias Laupichler on the analysis of self-perceived AI competencies of an AI course [pub:8].

Operationalization and Effects Competency frameworks are mostly collections of knowledge, skills, and attitudes, and are often not yet operationalized or validated in practice [153]. Moreover, it is often unclear what effects can be expected from this operationalization [255]. This is related to the finding of a systematic review by Almatrafi, Johri, and Lee [8], who note that AI competencies are often developed top-down by researchers and that there is a need for more bottom-up developments by understanding how users use AI in their respective domains.

This dissertation addresses the aspect of domain-specific AI competencies in the engineering context in Chapter 4 as well as touching on the operationalization at the program level in Chapter 5 and at the course level in Chapter 6. Building on the understanding of AI competencies, the next sections highlight the current state of the art in operationalizing AI competencies in curricula and courses.

3.3 Operationalizing AI Competencies through Curricula and Courses

Another way of looking at competencies is from a curricular structure. As discussed earlier in Section 2.2, curricula determine the content, process, and sequence of particular topics, subjects, or subject areas that are taught. Moreover, curricula can be described at two levels: the program level and the course level. The following section first focuses on the program level, before explicitly addressing AI courses in Section 3.3.4.

At the program level, there have been several approaches to defining guidelines for AI curricula, some explicitly targeting the development of AI competencies (e.g., the AI4K12 framework), others examining AI as a topic (e.g., the CS 2023 curricula). Curricula are often an operationalization of competency frameworks and include learning outcomes as well as connecting pedagogical considerations. In the context of K-12 education, a UNESCO report [309] analyzed different national AI curricula and aims "to guide the future planning of enabling policies, the design of national curricula or institutional study programmes, and implementation strategies for AI competency development" [309, p. 6]. The report identified five types of integration forms:

- *Discrete AI curricula*: developed in an independent subject
- *Embedded AI curricula*: embedded in other subjects (e.g., computer science or engineering)
- *Interdisciplinary AI curricula*: embedded cross-disciplinary
- *Multiple-modalities*: core requirements combined with independent learning or alternative extracurricular activities such as hackathons, competitions, or industry experiences.
- *Flexible AI curricula*: selection of one or more integration mechanisms

Another distinction is the number of hours devoted to the subject and whether an AI-related subject is required or elective. While these distinctions are aimed at the national K-12 curriculum, one can use this frame of analysis to contextualize the integration of AI education in disciplinary fields. Some examples of curricular guidelines at a broad level and in a disciplinary context are provided in Table 3.3.

Table 3.3: Overview of AI reference curricula.

Curriculum	**Target Group**	**Description**
AI4K12 [304]	K-12	Promoting foundational AI knowledge and skills for K-12 education
ML Education Framework [170]	K-12/Higher Education	Overview of ML principles
AI Literacy Design Considerations [191]	Curriculum Developers	Design considerations for AI education
CS Curricula 2023 [167]	CS students	Guidance for CS education including AI topics
CDIO Syllabus [203]	Engineering students and professionals	Guidance for engineering education, touching aspects of AI

3.3.1 Broad AI Frameworks and Guidance

There are several comprehensive AI curricula, frameworks, and guidelines that aim to provide a reference for curriculum design. The following focuses on three examples, namely the *AI4K12 curriculum* [303, 304], the *Machine Learning Education framework* [170], and the *AI literacy framework and design considerations* [191]. These have been chosen to highlight different aspects of the development and competency areas and the learning outcomes they suggest.

AI4K12 Curriculum

Although focused on K-12 education, the *AI4K12 curriculum* is a relevant source for understanding the foundations of AI curricula, as it is widely referenced and used in the community [304].

Development The US-based initiative, sponsored by the *Computer Science Teachers Association (CSTA)* and *Association for the Advancement of Artificial Intelligence (AAAI)*, formed a joint working group with *AI4All* to develop national guidelines for K-12 AI education, including classroom resources [303, 304]. Back in 2019, the initiative coined the "Five Big Ideas in AI" as a list of topics and competencies, along with resources distributed across grade levels and difficulty levels [303, 304].

Competency Areas and Learning Outcomes The five ideas [303, 304] include understanding of:

- perception of AI systems through sensors,
- how AI systems use representations of data for reasoning,

- the idea of learning from data as the core of ML,
- that AI agents need different kinds of knowledge to interact naturally with humans, and
- the positive and negative societal implications of AI.

The five big ideas are further detailed in four curriculum bands (grades Kindergarden to class 2, 3-5, 6-8, and 9-12), describing the progression of learning objectives (what students should be able to do) and enduring understandings (what students should know) per grade group as well as unpacking it into an example (see [url:3]) [304].

Machine Learning Education Framework

The *Machine Learning Education framework*, proposed in the dissertation of Lao [170], draws on educational theories of constructivism (learning is enhanced when students create personally meaningful artifacts), computational thinking and action (breaking down complex problems into manageable parts and applying algorithmic methods), and self-efficacy. It aims to transform ML consumers into ML contributors as participants in the field.

Competency Areas and Learning Outcomes The framework is structured around three core categories of knowledge, skills, and attitudes (see Table 3.4). It can be seen as a guideline and reference point to inform curriculum decisions. The competencies also relate to courses, where Lao [170] argues for six minimally required courses focusing on different aspects (marked with stars in the Table 3.4).

Accordingly, Lao [170] also proposed a curriculum rubric to help curriculum designers and educators assess either what they want to focus on at the beginning of a design process or the coverage of curricula and courses in the evaluation process. The rubric describes a rating scheme around the competencies from high coverage to minimal coverage [170, p. 112-121] and is exemplified for several courses and curricula. The rubric is therefore useful for comparison and benchmarking of courses [309].

AI Literacy Framework and Design Considerations

In their influential paper from 2020, Long and Margeko [191] propose 17 core competencies and learning outcomes related to AI literacy, as well as corresponding design considerations, based on a scoping study of the existing literature. To this end, the competencies aim to describe what a non-technical audience should know about AI and how to best teach it.

Table 3.4: The Machine Learning Education Framework [170], adopted from [309]. Asterisks indicate minimum required courses.

Category	Competency	Description
Knowledge	General ML knowledge*	Know what machine learning is (and is not). Understand the entire pipeline of the creation of ML systems.
	Knowledge of ML methods	Identifying when to use a range of ML methods across the breadth of the field (e.g., k-nearest neighbors, CARTs or decision trees, neural networks, ensemble methods). Understand how different methods work.
	Bias in ML systems	Understand that systems can be biased, and the different levels and ways in which bias can be introduced.
	Societal implications of AI*	Understand that ML systems can have widespread positive and negative impacts. Consider the ethical, cultural, and social implications of what they do.
Skills	ML problem scoping	Determine which problems can and should be solved by ML.
	ML project planning	Plan a solution that is sensitive to both technical and contextual considerations.
	Creating ML artefacts	Use tools to create appropriate artefacts.
	Analysis of ML design interactions and results*	Describe the explicit and implicit design intentions of an ML system. Critically analyze the intentions against how the system can and should be used.
	ML advocacy*	Critically discuss ML policies, products, and education.
	Independent out-of-class learning	Students seek learning experiences outside the classroom.
Attitudes	Interest	Students are engaged and motivated to study the topic.
	Identity and community	Students contribute to and learn from a community of peers and/or broader online communities who are interested in ML.
	Self-efficacy	Students are empowered to build new, meaningful things.
	Persistence	Students continue and expand their engagement with ML.

Development The competency areas and design considerations are all based on an exploratory literature review aimed at scoping the field. Other more recent studies build on their report to describe similar competency frameworks [8, 177]. However, to provide a holistic example, the competency areas and design considerations are presented here.

Competency Areas and Learning Outcomes An overview of the competency areas and learning outcomes is given in Table 3.5. Broadly speaking, they fall into similar categories to the approaches discussed previously, but take a more content-centred way of describing different content dimensions.

Design Considerations In addition to learning outcomes, Long and Magerko [191] also proposed design considerations for AI education, focusing on various elements that touch on pedagogical aspects as well as social dimensions. The 15 design considerations are presented in Table 3.6.

3.3.2 Reference Curricula in Computer Science and Engineering

In addition to general AI frameworks and curricula, we also explore how AI competencies are addressed in reference curricula for engineering education. In particular, the *Association for Computing Machinery (ACM) Computer Science Curriculum*, last updated in 2023, and the *Conceive Design Implement Operate (CDIO) syllabus*, last updated in 2022. While other accreditation bodies and standards exist, these provide a good overview of how AI education and competencies are addressed and developed.

ACM Computer Science 2023 Curriculum

The *ACM CS curriculum* [167] is a set of recommendations for undergraduate computer science education, developed through a collaborative process involving academics, industry professionals, and other stakeholders from leading computing organizations such as the *ACM*, *IEEE-Computer Society*, and the *AAAI*. The curriculum aims to provide a comprehensive framework for the knowledge and skills that computer science graduates should possess. It is intended to standardize core competencies across institutions, provide benchmarks for accreditation bodies, inform curriculum development, and assist educators in creating relevant course materials and syllabi.

Development The CS curriculum is typically updated every 5-7 years to keep up with the rapid changes in the field of computer science [78]. The most recent recom-

Table 3.5: AI literacy learning outcomes [191], adapted from [309].

Competency	Description
1. Recognize AI	Distinguish between technological artifacts that use AI and those that do not.
2. Understanding intelligence	Critically analyze and discuss the characteristics that make an entity "intelligent". Discuss the differences between human, animal, and machine intelligence.
3. Interdisciplinarity	Recognize that there are many ways to think about and design "intelligent" machines. Identify a variety of technologies that use AI, including technologies that span cognitive systems, robotics, and ML.
4. General vs. narrow AI	Distinguish between general and narrow AI.
5. AI strengths & weaknesses	Identify problem types where AI excels and where it does not. Determine when it is appropriate to use AI and when to leverage human skills.
6. Imagine future AI	Imagine possible future applications of AI and consider the impact of such applications on the world.
7. Representations	Understand what a knowledge representation is and describe some examples of knowledge representations.
8. Decision making	Recognize and describe examples of how computers reason and make decisions.
9. ML steps	Understand the steps involved in machine learning and the practices and challenges associated with each step.
10. Human role in AI	Recognize that humans play an important role in programming, model selection, and fine-tuning AI systems.
11. Data literacy	Understand basic concepts of data literacy.
12. Learning from data	Recognize that computers often learn from data (including one's own data).
13. Critically interpret data	Understand that data requires interpretation. Describe how the training examples provided in an initial data set can affect the results of an algorithm.
14. Action & reaction	Understand that some AI systems have the ability to physically act on the world. This action may be guided by higher-level reasoning (e.g., walking along a planned path) or reactive impulses (e.g., jumping backwards to avoid a detected obstacle).
15. Sensors	Understand what sensors are and that computers use sensors to perceive the world. Identify sensors on a variety of devices. Recognize that different sensors support different ways of representing and reasoning about the world.
16. Ethics	Identify and describe different perspectives on key ethical issues related to AI: privacy, employment, misinformation, singularity, decision making, diversity, bias, transparency, and accountability.
17. Programmability	Understand that agents are programmable.

Table 3.6: Design considerations for AI literacy [191], adapted from [309].

Design Consideration	**Description**
Explainability	Include graphical visualizations, simulations, and explanations of the agent's decision-making processes to enhance learners' understanding of AI.
Embodied interactions	Design interventions that allow individuals to act as or follow the agent to understand the reasoning process, using embodied simulations or hands-on experimentation with AI technology.
Contextualize data	Encourage exploration of data set origins, collection methods, and limitations, favoring data sets that are relevant to learners' lives and are messy or low-dimensional.
Promote transparency	Ensure transparency in AI design by eliminating black-box functionality and sharing creators' intentions, funding sources, and data origins.
Unveil Gradually	Prevent cognitive overload by allowing users to learn about system components incrementally, with options to inspect a few components at a time, and introducing scaffolding that fades as understanding grows.
Opportunities to program	Provide ways for individuals to program or teach AI agents while minimizing coding requirements through visual/auditory elements.
Milestones	Consider how developmental milestones (such as theory of mind) and prior technology experience influence perceptions of AI, especially in children.
Critical thinking	Encourage learners, especially younger ones, to critically evaluate AI technologies by questioning their intelligence and trustworthiness.
Identities, values, and backgrounds	Recognize how learners' identities and values shape their interest in AI and use culturally relevant elements to increase engagement.
Support for parents	Provide resources to help parents facilitate their children's learning experiences with AI in family settings.
Social interaction	Create AI learning experiences that encourage social interaction and collaboration among learners.
Leverage learners' interests	Use current events, personal experiences, or popular activities such as games and music to create engaging AI literacy interventions.
Acknowledge preconceptions	Address learners' preconceptions about AI that have been shaped by popular media, and find ways to respect and extend these ideas in educational contexts.
New perspectives	Include in educational materials diverse viewpoints that are less represented in mainstream media, including balanced discussions of the benefits and risks of AI.
Low barrier to entry	Communicate AI concepts in ways that are accessible to those without extensive math or computer science backgrounds, focusing on relatable content and reducing prerequisite knowledge.

mendations were published in 2024 (see [167]). The development process included a needs assessment through feedback from various stakeholders from academia, industry, and professional organizations [78]. It also involved curriculum design with a task force of experts who defined the core knowledge areas, learning outcomes, and recommended course content [78]. In addition, the proposed curriculum was shared with the broader computer science community for feedback and input, and revised based on the feedback received.

Competency Areas and Learning Outcomes The curriculum is organized in 17 knowledge areas, roughly divided into subfields of CS. The AI core knowledge area focuses on the study and application of artificial intelligence to solve complex problems that traditionally require human intelligence. It includes at its core [78, 167]:

- *Fundamental Issues*: Overview of AI problems and applications, definitions of intelligent agents, and problem characteristics;
- *Search*: State space representation, uninformed and heuristic search algorithms;
- *Representation and Reasoning*: Symbolic, logical, and probabilistic representations, Bayesian reasoning, and decision making under uncertainty;
- *Machine Learning*: Supervised, unsupervised, and reinforcement learning, data handling, feature representation, and model evaluation;
- *Applications and Societal Impact*: Practical applications in various domains, ethical considerations, including fairness, trust, and explainability.

It also describes areas that are not at the core such as probabilistic representation and reasoning, planning, logical representation and reasoning, agents and cognitive systems, natural language processing, robotics, perception, and computer vision [78, 167].

Further Considerations The authors of the curriculum emphasize that in implementing the AI knowledge area, a balance is needed between the study of still-used foundations (e.g., search or rule-based systems) and the desire to focus on cutting-edge AI and ML approaches [167]. In addition, they recognize that because AI as a field is rapidly evolving, educators must stay on top of current methods and developments to keep curricula and courses up-to-date [78, 167]. Eaton and Epstein even describe teaching AI as a moving target [78]. Finally, educators should ensure that students are well informed about the ethical and societal considerations and implications of applying AI methods and learn about them in the context of their applications [78, 167]. In the context of generative AI, the authors mention that the topic is attracting more interest in AI and other subfields. At the same time, they point out that there are currently still issues such as grounded perception, lack of explanation, or lack of guarantees of correctness that need to be resolved for broader applicability [167].

CDIO Syllabus

The *CDIO syllabus* is an educational framework tailored for engineering education, particularly in university and professional contexts [65, 203]. Established in 2001, the it was developed to provide a holistic understanding of the essential skills required for engineers to succeed in industry. It emphasizes not only technical competencies, but also the personal, interpersonal, and system-building skills necessary for today's engineering challenges. The CDIO syllabus is intended as a "reference framework that can be used to select goals for curricula and courses"[203, p. 2]. Its intention is, therefore, to provide a broad range of topics without being prescriptive [203]. The community initiative also has published CDIO standards to guide reform and evaluation of educational programs, but is not an accrediting body.

Development The CDIO curriculum is developed through collaboration among educational institutions, industry partners, and engineering education experts with the overall goal of aligning educational outcomes with the evolving needs of the engineering profession. After more than 10 years, the latest version of 2022 is the third revision and has been developed because of external drivers such as sustainability, digitalization, and acceleration as well as lessons learned from the implementation [203]. Changes were prepared in subgroups of experts and then discussed among CDIO member universities as well as in an international online working meeting.

Competency Areas and Learning Outcomes The overall syllabus is structured along the building blocks of (1) fundamental knowledge and reasoning, (2) personal and professional skills, and (3) interpersonal skills that support the(4) integrated CDIO process [65]. The most recent version includes an additional building block of (5) expansion that addresses competencies for subgroups of students. The CDIO syllabus does not explicitly address AI competencies, but it mentions the broader category of digital competencies, recognizing that "different digital systems have become vital tools in all engineering domains" [203, p. 7]. In addition, it emphasizes that an "important question is which data literacy skills shall be taught in the different fields of engineering education for future professionals and how these skills should be reflected in the CDIO Syllabus" [203, p. 7]. Given the broad and general target of the syllabus, the recent analysis of digital competencies was found to be scattered across the sub-themes and was therefore updated to reflect the impact of digital competencies [203].

From an implementation perspective, several papers apply the CDIO standards to AI-related curricula and courses. For example, Zéraï and Mosbeh [344] implemented a challenge-based course in an AI engineering program, and Ajailia [3] implemented a course on AI engineering ethics with the CDIO standards.

3.3.3 Implementations of Curriculum Initiatives

In addition to reference curricula, there are already implementations of AI curricula and transformation processes towards AI education that can be used as a reference to learn from and identify important drivers of integration. Cantú-Ortiz et al. [48] described a case study of the AI education strategy and programs at the Tecnologico de Monterrey, which is based on five strategic initiatives: (1) development of academic programs, (2) building of research capabilities, (3) dissemination through conferences and training seminars, (4) outreach through industry-university collaboration, and (5) internationalization to enhance exchanges. As influencing factors for the program, the authors mentioned internationalization and internships, employability, entrepreneurship, academic competitions, growth plans, industry and public sector funding, AI conferences, and industry partners.

Similarly, Southworth et al. [288] described the *AI Across the Curriculum* initiative at the University of Florida. The initiative is built on the pillars of (1) investing in computing and hiring AI-focused faculty, (2) developing AI pedagogy and including measures for it in the university quality enhancement plan, and (3) developing an understanding of AI literacy at the university. The last includes the targeted curriculum development next to the development of new academic programs, pathways, research experiences, and career development. Interestingly, in the context of this initiative, AI education is seen as relevant across disciplines [288].

Overall, AI education itself is often discussed in an interdisciplinary setting because of its roots in philosophy, neuroscience, psychology, cognitive science, and mathematics [220]. The complexity and multidisciplinarity of developing AI programs is also highlighted by the experience of Utrecht University's AI master's program [133]. Their curriculum is built around six core features: (1) courses are taught by multidisciplinary and interdisciplinary faculty, (2) engineering techniques and theory are used hand in hand, linking implementation to theoretical concepts, (3) students are given choice in assessment and presentation to allow for individual interests, (4) relevance to practice and industry is emphasized, (5) the multidisciplinary origins of machine learning are emphasized, and (6) skill levels are balanced. Similarly, Ng et al. [236] argued that AI literacy should not be seen as a specialized field under engineering, but as a competency for students from all disciplines and levels. In addition, How and Hung [123] suggested that AI education for Science, Technology, Engineering, and Mathematics (STEM) education is different from CS AI education. This connects to the differentiation of AI competencies in Section 3.2.

3.3.4 Teaching and Learning about AI

In addition to the integration of AI competencies into curricula in a broader sense, AI education can also be considered at the course level, including materials about AI. Here, AI education takes different forms, such as informal or formal learning experiences, and is aimed at different groups [8, 177, 233, 255, 272].

Types of Learning Experiences

According to the recent review by Pinski and Benlian [255], AI is taught through formal and informal learning experiences. On the formal side, one can distinguish between lecture-based formats [141, 341], exercise-based formats [159, 160, 341], and artifact-based formats [55, 141, 168]. Exercise-based formats appear in traditional forms as in-class exercises, homework, or term projects, but can also take interactive forms such as group projects, flipped classrooms, or storytelling [255]. Artifact-based formats use interaction with AI tools or the construction of custom AI models or features as part of the learning experience. For example, Kusuma et al. [168] designed an educational application where students learn about history and facial recognition, and Chiang and Yin [55] tested reliance on ML models in combination with a targeted intervention that allowed users to construct test datasets and evaluate model performance indicators. Other examples can be found in the systematic reviews [8, 177, 233, 255].

On the informal side, one can distinguish between community-based, self-directed exercise-based, and self-directed artifact-based approaches [54, 255]. Community-based approaches can take the form of book clubs [181], online forums, family learning conversations [192]. Self-directed, exercise-based approaches can be found in mobile learning applications or self-selected learning experiences [54, 347]. Meanwhile, self-directed artifact-based learning experiences refer to informal interactions with AI, for example in museums or art exhibits [115, 190], and to developing one's own small projects to learn about AI [54].

Overall, there are many different forms of learning experiences. However, it is still difficult to judge which learning methods are best suited for which learners [255]. Especially in the context of domain-specific AI education, learners come from different backgrounds and have different prior experiences that influence their learning trajectories and needs [255].

Content

Selecting the right content is another challenge in teaching about AI. Vazhayil [313] found that teachers do not know how to structure AI courses, and Lee et al. [180] added that teachers find it difficult to decide what to teach. In their review of AI teaching and learning, Ng et al. [233] recommended, among other things, that "more curriculum guides and frameworks are developed to support educators"[233, p. 21].

In analyzing implementations of AI literacy interventions, Almatrafi, Johri, and Lee [8] found that the majority of the implementations they analyzed addressed the knowing and understanding aspect, followed by using and applying, evaluating, and navigating ethically. Less attention was given to recognizing and creating.

Content selection has been of interest for some time. For example, in 2016, Wollowski et al. [337] surveyed educators and practitioners to capture current practices in AI education and proposed changes. Their findings are based on 37 responses from educators and 31 responses from practitioners. On the educator side, one finding was that 69% emphasized the lack of time as the biggest barrier to adding more topics to the AI curriculum. Other constraints included lack of appropriate learning materials (15%), and lack of student preparation or interest (12%). In the open comments section, four educators mentioned that the difficulty of teaching AI lies in the difficulty of choosing which topics to cover. A key difference observed between educators and practitioners was that practitioners suggested the ability to design a system as an important learning outcome, while educators seemed to focus on simple toy problems in their introductions. Furthermore, practitioners highlighted the ability to take the perspective of AI tools and techniques, while educators took a broader perspective of historical roots and ethical issues [337].

Overall, this demonstrates the complexity that educators face when selecting content and structuring courses. Educators are faced with a wide range of content options, pedagogical approaches, and student and practitioner needs. Moreover, especially in domain-specific AI education, which emphasizes the interdisciplinary nature of AI, educators themselves often need to learn about AI. A study of informal learners concluded that “despite being highly motivated and investing a lot of time and effort, many of the informal learners of ML in our study felt overwhelmed and struggled to keep up.” [54, p. 9]. This underscores the challenge that educators face in the fast-paced field of AI education.

3.3.5 Teaching and Learning with AI

To provide a holistic perspective on the topic, it is also important to provide a brief overview of the use of AI tools in learning activities and assessment. Although not the focus of this dissertation, the area of using technology in learning is driving a lot of discussion. As argued in the following, AI-related skills and knowledge in curricula are closely related to the adoption of assessment formats and learning opportunities. This subsection is based on the paper [pub:6] written together with Maria Klar as well as on several workshops and experiences with educators in higher education [pub:13, pub:14, pub:21]. The aim is to provide a holistic perspective on aspects of using AI in teaching and learning, linking the aspects of what to teach to how to develop appropriate assessment methods and learning activities. This perspective is relevant because it is closely related to the relevance of teaching about AI.

The use of AI in higher education can be roughly structured along the categories of assessment and evaluation, prediction, AI assistants, intelligent tutoring systems, and student learning management [31, 66, 343]. Following the idea of constructive alignment, the interconnection between competencies, assessment, and teaching and learning activities [21], we can further focus on AI and assessment as well as AI in teaching and learning activities.

AI and Assessments

If we assume that new knowledge, skills, or attitudes related to AI will be included as teaching and learning objectives in higher education curricula, these teaching and learning objectives must in turn be taken into account in the design of assessment scenarios. For example, it is becoming clear that writing practices may change more than before with generative language models, LLMs. Courses that focus on writing skills, for example, should offer learners the opportunity to try out the reflective and effective use of AI, especially LLMs. However, these tools should not be excluded from assessment. This can be a challenge, as AI-based tools may provide (too) much of the performance required in an exam.

LLMs are already capable of producing longer pieces of explanatory, argumentative, or reflective text. The context window, i.e. the amount of input and output that can be processed by a LLM, is constantly growing. This allows longer texts with increasing complexity to be generated automatically. It is possible for learners to submit AI-generated texts as their own work without any software that can recognize them reliably and without discrimination [148, 185]. Thus, traditional homework is no longer a reliable instrument for certifying learning. The question of permissible aids is not new: in mathematics, for example, there is an ongoing debate about the use of calculators [224], and open-book exams are used in universities [39]. However, LLMs are more than just an aid here, but a tool to generate common exam performance at a passable level with relatively little human input [200].

There are at least two - equally incomplete - answers to the question of how to deal with AI as a tool in assessment contexts [45, 46]: On the one hand, one can try to exclude AI tools from exam situations and make exams cheat-proof, e.g., by returning to face-to-face exams. The latter would focus more on the goal of fair certification of performance, but would be a didactic limitation given the limited ability to make more complex skill contexts visible in this format. Alternatively, LLMs and other AI tools can be incorporated as new tools, and exam formats can be made complex enough to challenge learners to work with and go beyond the generated results. This can be achieved, for example, through group assessments, oral defenses, or project exams. Such assessment formats would focus on the goal of skill acquisition and the relevance of exams to everyday life, but can be resource-intensive.

Furthermore, AI could help reduce the correction burden of more complex assessment formats. There has been many years of research into automated assessment of exam performance, particularly in the US, where essays and term papers play a major role [248, 262]. Ironically, AI systems may now increasingly evaluate essays written by AI systems.

In addition to reducing the effort involved in examinations, AI can also be used to support learning processes. Corrective assistance could give teachers more freedom to provide not only summative but also more frequent formative feedback, referring to feedback during the learning process [345]. Such formative feedback could also be supported by AI (cf. [20]). Another example is the development of analytic tools that evaluate the learning process in small steps and provide feedback to the learner, often referred to as learning analytics [128]. However, one challenge of these learning analytics tools is still to perform qualitative, in-depth analyses that go beyond click behavior on learning platforms and the evaluation of short tests [291].

Even in standardized domains such as programming, in-depth analysis of learning processes is still time-consuming, partly because a large amount of high-quality data is required to train the models [60, 63]. It is still unclear to what extent general LLMs can be adapted for the analysis of learning processes.

The situation that generative AI requires a re-evaluation of previous testing formats can be seen as positive in that it could provide a tailwind for previous attempts at reform. Generative language models act as amplifiers of previous discourses without raising entirely new problems and questions. The question of forms of assessment that are both competency-oriented and reliable, and that can be carried out with limited resources, is once again emphasized by the advent of AI.

If the competency goals in a discipline change, or if interdisciplinary competencies are emphasized more strongly, this should be reflected in the forms of assessment. Forms of assessment that test these competencies in an everyday context are currently still associated with an increased correction effort, which could be facilitated by (partially) automated AI assessments. Formative assessment, which would also be desirable, is also connected to efforts. Thus, the question of how formative and possibly summative assessment can be supported by AI remains. To this end, generative AI reinforces existing questions in the area of assessment in higher education.

AI in Teaching and Learning

If AI in general, and generative language models in particular, are to be given a greater role in competencies, assessment, and feedback, then their role in teaching and learning must also be reflected. For example, if AI-supported literature searches play an increasing role in writing scientific texts (a change in competencies), then the ability to use AI-supported search tools appropriately should not only be used in the assessment situation, but there should also be opportunities for practice and reflection. This requires free access to AI tools so that all students and educators can use them equally. For example, the University of Michigan has made several AI tools available to all members of the university [url:5]. However, AI tools should be used not only where they are immediately necessary to achieve an AI-related teaching and learning goal. They also offer the long-term potential to support teaching and learning processes in ways that were previously not possible because of limited human resources.

At the same time, the promise of AI-assisted learning has been around for a long time and is still waiting to be realized [31, 343]. Before the advent of generally available generative AI, there was no widespread use of AI in teaching-learning settings, at least in the German-speaking world. Individual applications use machine learning for adaptivity, but so far there is no system that is widely used in schools or universities. AI is sometimes used in intelligent tutoring systems, learning analytics, or chatbot support [31, 226]. However, these systems are often still rule-based because training specialized models is time-consuming, as described above. Especially in intelligent tutorial systems, the task of the AI is not to write but to read, for example, to automatically evaluate the learning status. The idea is that, based on this analysis, the learner receives personalized content that is as appropriate as possible, with the content itself usually being created by humans.

Personalized Learning In the context of LLMs, there is often discourse of personalized learning made possible by AI, although generative AI can only analyze learning status in a rudimentary way at best. LLMs do not develop a learner model, meaning they do not analyze the learner's current level of knowledge and do not proactively deliver the appropriate learning content. They are also not adaptive learning media per se. This means that no data is collected about the learner for a learner model and no decisions are made by the system for the learner. Therefore, generative AI cannot be considered an adaptive learning medium, but an adaptable one. The primary strength of generative AI lies in the capability that texts can be adapted by learners in terms of parameters such as form, length, language, difficulty, or content focus. This was previously not possible with any tool. Thus, while previously learners had to search for the best way to present content, they can now, for example, have a script summarized or a difficult passage of text explained in a simplified way.

LLMs in the Learning Scenario To this end, LLMs open up a new learning method, that is a way of acquiring knowledge and skills in a targeted way. Learners are no longer dependent on the availability of information in a certain form of presentation, but can adapt it to their own needs. At the same time, learners may need some support to use AI effectively for these purposes and to be aware of its limitations. Otherwise, there is a risk that, with too little prior knowledge, they will not use these tools specifically for learning and will not benefit from them [19]. According to a study by the Boston Consulting Group [url:6], consultants with less prior knowledge benefited most from working with ChatGPT on creative tasks. However, they also relied more on the results and therefore performed worse on a task where ChatGPT provided misleading results.

So far, generative AI has not led to completely new teaching methods, but has been integrated into existing teaching methods [143]. For example, a chatbot can take on a role that would otherwise remain empty, such as a discussant, feedback provider, or even a role in a role-playing game like a simulated consultation. Roles that facilitate interpersonal communication are also conceivable: AI could summarize a discussion at the end of a seminar or even moderate it. The latter seems technically difficult at present, but could become feasible with further multimodal capabilities.

LLMs as Additional Actor Chatbots can, therefore, be used as additional actors in the learning scenario, where this protagonism goes beyond the use of a new medium [120]. In this context, the term "actor-like" means that chatbots are able to respond to user input and mimic interpersonal interaction to a greater extent than previous technologies. Generative chatbots are not rule-based, which means they do not act deterministically, resulting in a complex interaction situation that is not subject to a clearly recognizable cause-and-effect relationship, even with expert knowledge. The effects of one's own inputs can only partially be reconstructed in retrospect [223]. In addition, new models are constantly coming onto the market, each of which behaves differently, so that the changes in the interaction must be tested anew. Regarding the actor-like nature, the question arises as to what degree of anthropomorphization is desirable [url:4], especially since a humanoid chatbot interface can hide the reality that all interaction data potentially goes to the companies behind it. The challenge here is to promote and provide (open) language models, ideally running locally on devices, so that users have control over data flows and interfaces. Another question is the social implications of AI as an additional actor. How does the interaction between teacher and learner change in a triangle with AI? To what extent does the responsibility for the learning process shift?

According to constructive alignment, dealing with the affordances of this new tool and the new actor in teaching-learning settings is a necessary building block in view of the changes in the area of competencies and examinations. As learners and educators try out and reflect on generative AI in different contexts, competencies are built in this new area of learning. In exams, learners can show how they use generative AI or how they do without it. However, AI can play a role not only as a tool and therefore as learning content, but also as a support in areas that were previously left unfilled because of limited resources. In teaching-learning settings, the actor-like nature of generative AI systems becomes apparent with increasing multimodality, and questions arise about the characteristics of these new actors and the possibilities and limitations of their use.

Summary

With respect to generative AI, the interconnectedness of competency objectives, assessment formats, and didactic decisions is also evident in accordance with constructive alignment. This also underscores the complexity that educators and curriculum developers face. If AI competencies are to be integrated into curricula, this necessarily entails integration into assessment scenarios and teaching-learning settings. Similarly, when AI is integrated into assessment scenarios and teaching-learning settings, consideration should be given to teaching and learning about AI.

3.3.6 Challenges

AI education can be positioned as a subfield of CS education, and as such as a skill applicable across disciplines [202]. However, compared to the accumulated evidence in other aspects of CS education, such as programming, the field of AI education is still underexplored. While there are many examples, there is currently no systematic understanding of AI education in terms of which teaching approaches are most effective for which audiences. In addition, curricular initiatives are still rare and their impact is still unknown. Much work remains to be done on the impact of AI on teaching and assessment processes and on the content of teaching about AI.

These observations connect well with the lessons learned from the development of the AI part of the CS 2023 curriculum [78]. In this context, the authors highlight the widely differing opinions on the content of an AI curriculum and how much time should be allocated to it. They also highlight the rapid pace of AI developments as a challenge to setting a curriculum that will remain current, and the challenge that societal and ethical issues are intertwined with applications [78].

3.4 Empowering Educators in Integrating AI Competencies

As described in Section 3.1, faculty and leadership play an important role in integrating AI competencies and are at the center of change efforts and digital transformation. Educators serve as role models for students' use of technology as well as facilitators for building AI competencies [131]. In a recent empirical study of AI integration in higher education teaching practices and faculty needs, Mah and Groß [199] found that faculty perceive potential improvements in educational equity as the greatest benefit, which is consistent with findings from a meta-study by Bond et al. [31].

Two Perspectives As described in the previous sections, educators face two main challenges or demands when it comes to AI. On the one hand, they need to *adapt their teaching process*, for example by integrating AI into their routine and learning activities or by changing their forms of assessment (see Section 3.3.5). On the other hand, they need to consider *curricular changes* to prepare their students for the future workplace.

A theoretical model to contextualize this idea is the Technological Pedagogical Content Knowledge (TPACK) model [221, 222]. TPACK is a widely used framework developed to identify the knowledge educators need to effectively integrate technology into their teaching [222]. The three components are (1) content knowledge (CK) (understanding of the subject matter to be taught), (2) pedagogical knowledge (PK) (knowledge of teaching methods and how students learn), and (3) technological knowledge (TK) (familiarity with various technologies and how they can be used in the classroom) (see Figure 3.4). Thus, when it comes to AI, educators need to adapt their content knowledge, but also learn how to use technology in the classroom.

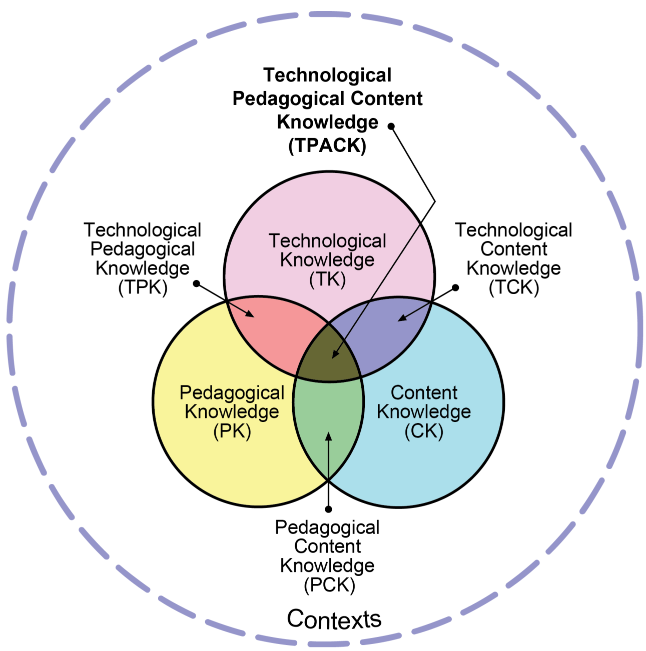

Figure 3.4: TPACK diagram reproduced with permission of the publisher, © 2012 by tpack.org.

As described in Section 3.1, curriculum change does not occur in a vacuum, and faculty commitment to changing aspects of their curricula depends on multiple factors [172]. Building on existing research, Lattuca and Polland [172] conceptualized these influences in a model of faculty decision making about curricular change (shown in Figure 3.3 earlier). The focus here is on understanding content change and what influences faculty decision making about curriculum change. It also emphasizes the importance of educators' knowledge, beliefs, and experiences.

Educators' AI Competencies A recent meta-review on AI and education highlighted educators' (technical) knowledge as a key challenge [31]. This may be because of the situation that educators have not been the focus of research on AI in education [343]. In addition, AI competencies and AI literacy is a relatively new concept that has only gained traction since 2020 [233]. Focusing on the perceived benefits and challenges of AI-based tools in teaching and learning among university faculty, Groß and Mah [199] identified four profiles of educators in higher education:

- the *optimistic faculty*, who mostly agree with the benefits and disagree with the challenges,
- the *critical faculty*, who are critical of the use of AI-based tools and tend to somewhat disagree with the benefits and agree with the challenges,
- the *critical faculty*, who agree with the perceived benefits but are also critical of the challenges of AI-based tools,
- the *neutral*, who rate both benefits and challenges as low.

Overall, this study highlights the diversity of thought and opinion among faculty. The study also found that faculty with high AI self-efficacy who are also classified as optimistic are likely to use AI more effectively than those who do not share this profile [199], while such a relationship was not significant for the other profiles. This is consistent with findings on self-efficacy [4, 15], which argue that perceived self-efficacy influences teachers' intentions to use technology [275] and may moderate trust and ethical concerns. In terms of competencies, a recent study among students and faculty at the University of Hamburg found that the self-assessment of knowledge about AI is neither confident among educators nor among students, with "most groups indicate that they can explain the functioning of AI 'approximately', while other responses document a lack of knowledge" [16, p. 53, translated].

Several competency frameworks for educators have been developed [216]. Examples include the *UNESCO AI Competence Framework for Teachers* [311] or the *AI-PACK* [193]. However, a recent critical review of AI competency frameworks for educators [216] provided a critical overview and highlighted several areas that should be addressed:

- *Integration with digital literacy frameworks*: Assuming that the role of AI extends beyond traditional technology, there is a need to coordinate competency development with the development of other digital competencies, e.g., through prerequisites or progression benchmarks.
- *Subject-specific AI competencies*: While AI competencies are often seen as cross-curricular, there is a growing argument for domain-specific competencies. This argument is supported by disciplinary approaches to education (e.g. mathematics education). It also supports the notion that educators need both deep subject knowledge and AI expertise to effectively support students.
- *Implementation models*: AI competency frameworks for teachers should include clear implementation models that detail the stages of AI adoption, tailored to specific technologies and educational contexts. Resources such as funding, infrastructure, and teacher training are critical to successful implementation.
- *Ongoing development*: There is no ideal AI competency framework, and its effectiveness will depend on how well it aligns with the necessary competencies for educators. To refine these frameworks, an ongoing interdisciplinary dialogue is essential to ensure that educators have a mix of pedagogical skills, subject matter expertise, digital literacy, and AI skills for technology-enriched instruction.

While these are contextualized with a focus on using AI in teaching and learning and engaging educators at different levels, the findings also underscore the complexity of developing appropriate competency models.

Professional Development Offers In contrast to teacher education for K-12 education on AI [23, 290], professional development for faculty and educators in higher education has not been systematically studied. Mah and Groß [199]'s study of university faculty found that many faculty members expressed a strong interest in AI-related training, particularly in formats focused on teaching and learning with AI tools (78.5%), specific AI tools (66.4%), and using AI in research (48.6%). Overall, study participants planned to invest between 5 and 20 hours in professional development activities focused on AI, with about half indicating that their motivation was to learn about AI-based applications for teaching and learning. However, the focus of this study was on the use of AI-based applications for teaching and learning, not on changing content related to AI.

This is consistent with the results of a recent survey of 102 educators at the University of Hamburg [16], which highlights that educators are most interested in learning about tools (55) and staying informed about current trends and innovations (46), underscoring the dynamic nature of the AI topic. About a third of educators indicate a need for training on prompting, training on legal and ethical aspects, and general AI competencies and practical application cases [16].

Interestingly, the study also indicates that the most common channel for professional development on AI is informal exchange with colleagues (34 of 102 educators), followed by internal training offered by the institution (25 of 102), and self-study materials (19 of 102) [16]. While these experiences cannot be generalized across contexts and institutions, they highlight the complexity of the challenge of empowering educators through guidance and training. With generative AI, and in particular LLMs, being prominent in discussions over the past two years, many educators focus on the influences of AI on their teaching process. However, although it has been recognized as a challenge and a recommendation [31, 129], to date there seems to be no systematic effort to question or change the content of subjects and work on curriculum development. Thus, contextualizing these observations in the two perspectives, it can be concluded that the current focus is on adopting teaching processes and not on changing curricula.

Context Factor Another challenge for the professional development of educators lies in the differences between domains. Luckin et al. emphasized that the importance of contextualizing AI education for different sectors, workplaces, and professions "is essential due to the multiple intricacies, sensitivities and variations between different sectors and their settings, which all impact the application of AI"[194, p. 1]. Thus, both the application of AI and the teaching of AI are domain-specific and likely require both an understanding of the domain and an understanding of AI. Moreover, the application of AI touches on several transdisciplinary related issues such as ethical considerations, social implications, sustainability, and interdisciplinarity.

3.5 Contributions

This chapter first provided an overview of the systems perspective (Section 3.1) and highlighted the challenges of integrating AI competencies into engineering education (Section 3.1.5). In addition, the chapter described the current state of the art in conceptualizing AI competencies (Section 3.2) along the lines of generic, domain-specific, expert, and ethics-related AI competencies. It also discussed the operationalization of competencies in curricula and courses (Section 3.3), highlighting targeted and broad curricular frameworks and different forms of implementation.

Finally, the chapter also discussed the challenges from the perspective of educators (Section 3.4) who are faced with the demands of integrating new content and changing learning and teaching activities.

The following empirical work of the dissertation addresses the issue of integrating AI competencies in engineering education on three different levels. First, building on the identified gap in the conceptualization of domain-specific AI competencies, it contributes a conceptualization of an interdisciplinary competency profile at the intersection of AI and engineering (Chapter 4). Second, the state of the art showed the complexity of addressing AI competencies at the curricular level. Thus, this dissertation contributes to the conceptualization of a process for developing an interdisciplinary undergraduate program in AI through a curriculum workshop approach along with a validation of the program development and outcome (Chapter 5). Third, at the course level, the dissertation addresses the complexity faced by educators in integrating AI competencies into their discipline-specific courses. In particular, it contributes a structural guide for educators to support them in the development and co-creation of domain-specific AI courses (Chapter 6).

Overall, the dissertation contributes to theoretical and practical knowledge along different levels of the educational ecosystem. The following chapter deals with the conceptualization of AI competencies for engineering education, before moving on to the operationalization of the curriculum and course level in the following chapters.

4

Developing and Validating an Interdisciplinary Competency Profile for AI in Engineering

Connecting to the state of the art in AI education, there is a gap on anchoring AI competencies in the domain. This chapter focuses on the application domain of engineering education. While the use of AI in engineering is not new [281], there is a need to conceptualize and define the necessary domain-specific AI competencies for engineering.

This chapter proposes a competency profile for AI in engineering that focuses on the expertise of working with AI systems in the context of engineering. Based on perspectives from the literature and interviews with experts from industry and research, the most important sets of competencies in the areas of technical, methodological, social, and self-competencies are highlighted. Furthermore, competency statements are developed from these clusters and validated through a content validity survey with a panel of experts from industry and academia. The chapter builds on the published work of [pub:12].

4.1 Research Context

Contextualizing Competency Definitions This chapter focuses on the definitions of domain-specific AI competencies. To provide the research context, we first discuss these in the system model, illustrated in Figure 4.1.

Competency definitions are influenced by societal and industry needs as well as technological developments. They can inform international and national standards or national curricula (often more at school level). They also inform the development of programs, in particular the degree profile and curriculum, as well as course learn-

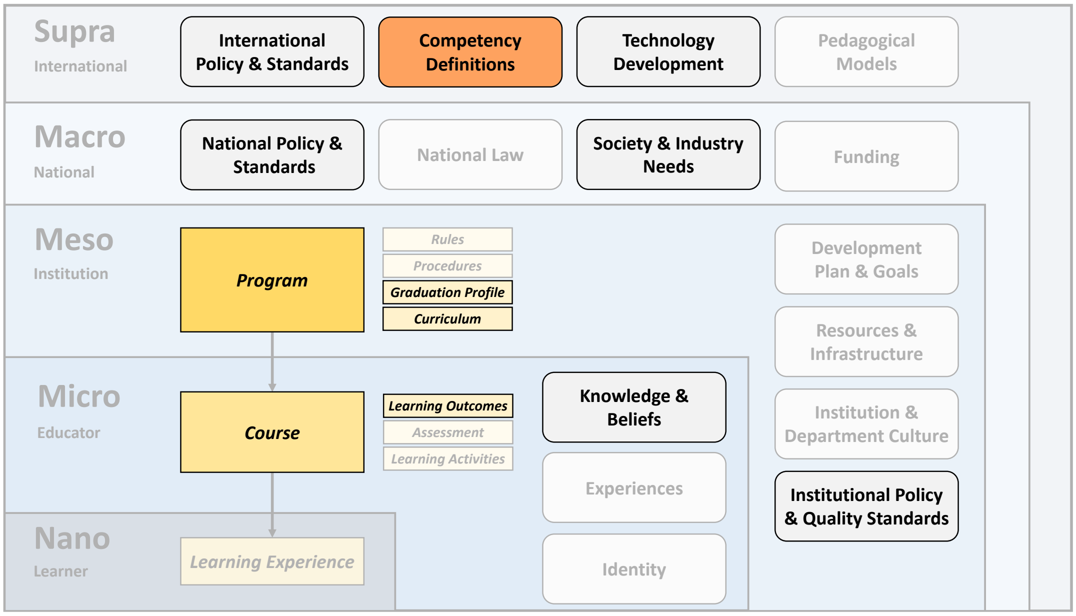

Figure 4.1: Competencies in the system model of influences on programs, courses, and learning experiences at different levels. The visible light gray boxes indicate relevant influencing factors that influence or inform the competency definitions.

ing outcomes. They may also inform institutional policies and quality standards, as well as the knowledge and beliefs of educators.

As discussed in Section 3.2, several authors have formulated sets of AI competencies for different target groups [8, 177, 255]. However, there is still no consensus on what AI competencies entail [177, 255]. Moreover, there exists only a few conceptualizations of domain-specific AI competencies in the disciplines based on use cases and roles [153, 255]. In summary, there is a need to define and develop domain-specific AI competency profiles that can be used to educate students and employees in their disciplinary contexts.

Need for Competency Definitions for AI and Engineering As contextualized in the state of the art Section 3.2, AI and digital tools are also changing the competency profiles of the next generation of engineers. With AI as an enabling technology in multiple use cases, there is a growing interest in applying AI to engineering applications such as energy efficiency, process optimization, quality management, and predictive maintenance [252]. At the same time, the value of digital innovation and data-driven processes lies at the intersection of disciplines [12, 113]. Thus, more than ever, interdisciplinary learning is required, integrating competencies across the boundaries of disciplines [99, 114].

Recent studies have investigated the changing competency requirements in engineering [1, 99, 113, 114], competency requirements for developing and working with AI [11, 12, 125, 329], and general future skills [336]. However, there is currently no conceptualization of what competencies are needed across disciplinary boundaries to work and develop solutions at the intersection of AI and engineering. Furthermore, established engineering competency profiles, such as the CDIO curriculum [203], Accreditation Board for Engineering and Technology (ABET) [url:1], and European Accredited Engineer (EUR-ACE) [url:2], do not yet address the integration of AI competencies in engineering curricula.

This chapter focuses on the question of *how to conceptualize domain-specific AI competencies in the application domain of engineering*. Here, competencies are used as the ability to act in and cope with context-specific demands [273], focusing on addressing technical, methodological, social, and self-competences (cf. Section 2.1). Thus, we can specify the research question as: *What professional, methodological, social, and self-competencies do engineering students need to work with AI systems?* (RQ 1). The chapter hypothesizes that the next generation of engineers will not focus on a single domain, but will need an interdisciplinary skill set that includes digital and AI competencies.

Contributions and Structure This chapter addresses domain-specific AI competencies in engineering by developing and validating a competency profile at the intersection of AI and engineering. First, competency clusters are identified from the literature and eleven interviews with experts from industry and academia. Second, competency statements are defined and validated through a content validity approach with 32 experts. The identified competency profile is intended to be a reference point for further adoption of engineering curricula in the future and a guide for engineers who want to upgrade their skills.

The chapter is structured as follows: Section 4.2 describes the methodological approach and research design of the studies. Next, the results of each step are presented, with Section 4.3.1 presenting the competency clusters identified from interviews and literature, and Section 4.3.2 describing the results of the content validity study. Finally, Section 4.4 contextualizes the findings within the broader research.

4.2 Methods and Material

In developing the competency profile for AI in engineering, a stepwise approach was followed according to Boateng et al. [28] and Marelli, Tondora and Hodge [205]. The research design is shown in Figure 4.2, structured along two studies. The first part focuses on identifying relevant clusters to generate an initial set of competency statements, while the second part aims to establish the content validity of these competency statements. The detailed data collection and analysis steps are described in the following.

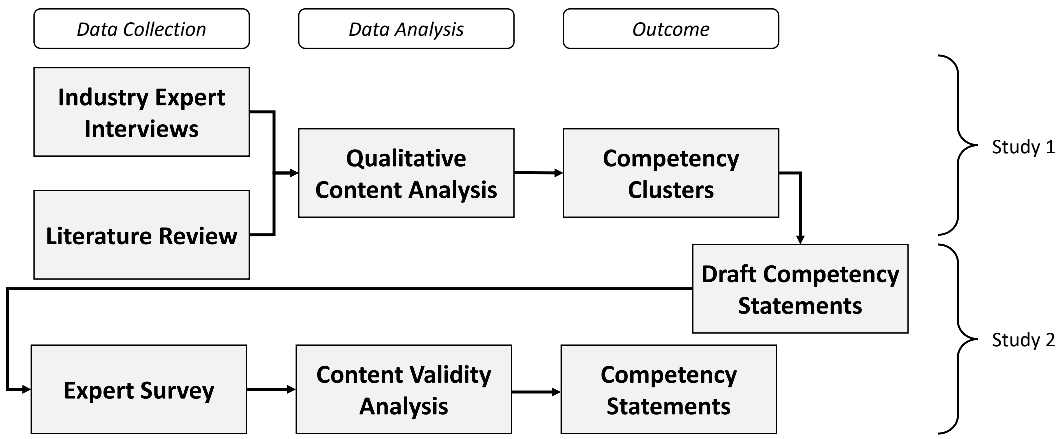

Figure 4.2: Research design overview for the identification of AI competencies for engineers, which includes two steps: first identifying relevant competency clusters through industry interviews and second validating derived competency statements with experts from academia and industry.

4.2.1 Study 1: Identifying Competency Clusters

To understand current engineering practices and related competencies, semi-structured interviews were conducted with engineers working at the intersection of AI and engineering. In addition, recent literature and technical reports from industry associations that provide an overview of the required competencies were reviewed.

Literature Selection The literature was selected using various search terms such as “competence”, “competency”, “skill”, “engineering”, “artificial intelligence”, and “machine learning”. The search was conducted in February 2022. Scientific studies, as well as white papers and association reports, were considered to reflect a broader industry perspective. German and English sources were used. In total, nine different sources [1, 11, 12, 99, 113, 114, 125, 329, 336] were selected and evaluated, most of which are also based on literature reviews and qualitative interviews.

Interviews For the expert interviews, eleven industry experts from different industries working at the intersection of AI and engineering were selected, see Table 4.1 for an overview. The companies included manufacturers of logistics systems, engineering service providers in mechanical engineering and IT, pharmaceutical companies, automotive manufacturers, applied sciences, and IT consultancies. In addition to the different industries, it was taken into account that the interviewees came from small, medium, and large companies, and that they performed functions in different areas (data science, strategic business development, IT strategy, software development, collaborative factory, business process management, consulting).

Table 4.1: Overview on interview participants of industry experts and practitioners.

ID	Job Title and Company
P1	Head of Data Science, manufacturer logistic systems
P2	Strategy Manager, welding company with 35 people
P3	Head of IT, pharmaceutical company
P4	Head of IT, engineering service provider
P5	Developer, IT service provider
P6	Head of Data Science, automobile manufacturer
P7	IT-Consultant, applied research institution
P8	CEO, IT service provider
P9	Manager Supply Chain, medical technology company
P10	Consultant, AI consultancy
P11	Manager, IT service provider

The interviews were conducted between February and March 2022. The interview questions focused on the general understanding of AI, current and future use cases in the companies, challenges in the use of AI, and the question of competencies required in the field of AI and engineering. The questionnaire can be found in the Appendix A.1. The interviews were recorded and transcribed for the analysis.

Data Analysis Both the expert interviews and the literature sources were evaluated using qualitative content analysis [208]. The competencies were identified, coded, and assigned to the competency areas of professional competencies, methodological competencies, social competencies, and self-competencies. Finally, subcategories were formed and the most frequently mentioned competencies were selected and described as clusters of the competency profile. Note that the interview data were reanalyzed compared to [pub:12] to provide more depth and detailed assessment.

4.2.2 Study 2: Establishing Content Validity

Building on the competency clusters and identifying the relevant competency statements, a content validity study was conducted with an expert panel of 32 practitioners at the intersection of AI and engineering.

Item Generation Based on the initial competency clusters, a set of items was formulated along the competency clusters. The wording reflected the definitions and mentions in the interviews. Three items were formulated per competency area, resulting in 33 competency statements, see Appendix A.2.

Panel Characteristics The characteristics of the expert panel are described in Table 4.2. Overall, the majority (79%) of the 32 experts reported either a deep or very deep understanding of AI. In addition, three-quarters of the experts worked with AI technologies almost every day or every day. Half of the participants have been working with AI for 3 to 10 years, while one-third have more than 10 years of experience in the field. Furthermore, half of the participants identified their domain as computer/software, while the other half come from other engineering fields.

Table 4.2: Characteristics of subject matter experts for content validity, where N is the number of people who chose that response option and % is the percentage of the total sample of 32 experts who chose that response option.

Response Options	N	%
AI expertise and experience		
No AI knowledge/experience at all	0	0%
Basic idea of what AI is	1	3%
Good understanding of how AI works, where it is used	6	19%
Deep understanding of AI[1]	12	38%
Very deep understanding of AI[2]	13	41%
Frequency of engagement with AI		
Almost never	0	0%
Less than once a week	1	3%
Approximately once a week	7	22%
Almost every (working) day	11	34%
Every day	13	41%
Since when do you engage with AI?		
0 to 1 year	0	0%
1 to 3 years	5	16%
3 to 10 years	16	50%
More than 10 years	11	34%

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[1] conducted initial AI research/development/knowledge accumulation
[2] several years of intensive AI research/development/knowledge accumulation

Table 4.2 – continued from previous page

Response Options	N	%
Age		
18 to 29	8	25%
30 to 39	0	0%
40 to 49	11	34%
50 to 65	9	28%
Older than 65	3	9%
Gender		
Female	4	13%
Male	26	81%
Other/Not specified	2	6%
Highest level of education		
Secondary school leaving certificate	0	0%
High school diploma	0	0%
Bachelor's degree	3	9%
Master's degree	12	38%
Doctorate/PhD	10	31%
Professorship	7	22%
Type of employment		
Student	1	3%
Employment at research or educational institution	15	47%
Employment at a company	14	44%
Self-employed	2	6%
Other	0	0%
Engineering domain		
Aerospace	0	0%
Biomedical	1	3%
Chemical	0	0%
Civil	0	0%
Computer/Software	15	47%
Electrical	2	6%
Environmental	0	0%
Industrial	7	22%
Materials	0	0%
Mechanical	2	6%
Nuclear	0	0%
Petroleum	0	0%
Other	5	16%

Procedure To establish content validity, the expert panel was presented with the initial set of 33 items organized into eleven domains. The experts were asked to rate the relevance and clarity of each item, as well as any additional improvements or suggestions for each area. Ratings were collected on a four-point Likert scale according to Davis [69]. Relevance was rated as follows: *1 - not relevant*, *2 - somewhat relevant*, *3 - quite relevant*, and *4 - very relevant*. Clarity was rated as *1 - not clear*, *2 -*

item needs some revision, *3 - clear but needs minor revision*, and *4 - very clear*. The study was conducted in September 2024 using the questionnaire tool Limesurvey. The set of items and questionnaire is presented in Appendix A.2.

Data Analysis Overall, content validity was determined by several measures. The mean and standard deviation were reported per item (competency statement) for both relevance and clarity. In addition, the Content Validity Index (CVI) per item (I-CVI) was calculated as the proportion of experts who rated the item as 3 or 4 (*quite relevant* or *highly relevant*). Similarly, the clarity rating was calculated as the proportion of experts who rated the item as 3 or 4 (*clear* or *very clear*). As consensus criteria, the analysis followed Lynn [196], who recommended I-CVIs of no less than .78 for an expert panel, but extended the criteria to include items that received a mean score above 3.0 for both relevance and clarity. In addition, the sample content validity index (S-CVI/Ave) was reported as the average of the I-CVI scores across all items.

4.3 Results

4.3.1 Study 1: Competency Clusters for AI Competencies in Engineering

The following section provides an overview of the identified competency clusters and the supporting literature and interview excerpts. The clusters are summarized in Table 4.3.

Table 4.3: Overview of competency clusters along professional, methodological, social, and self-competencies with supporting literature and interviews along with sample quotes from the interviews.

Category	**Supporting Literature**	**Supporting Interviews**	**Interview Quotes**
Professional Competencies			
Data and AI Knowledge	[1, 11, 12, 99, 114, 329, 336]	P1, P2, P3, P4, P5, P6, P7, P8, P10, P11	"If a data scientist is not also involved in data engineering, so to speak, does not know where the data comes from, how the data is collected, etc., then that is a problem." [P1] "The basic understanding of what form of machine learning there is, what models there are, what form of machine learning [...]" [P5]

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Category	Supporting Literature	Supporting Interviews	Interview Quotes
IT Competencies	[1, 11, 99, 113, 114, 329]	P2, P3, P4, P5, P6, P7, P8, P9, P10, P11	"Programming is never a mistake because then you understand how certain things are done and what works and what doesn't." [P2] "You need to know how to develop and implement AI applications." [P5]
Interdisciplinary Domain Know-How	[1, 12, 99, 113]	P1, P2, P3, P6, P7, P9, P10, P11	"If I could wish for an ideal student now, it would be 30% domain knowledge and 70% AI knowledge." [P6] "Having a technical understanding of what's going on, of the plant, of the business process; end-user understanding; having a basic understanding of technology, what's going on in this company" [P10]
Methodological Competencies			
Process- and Systems Thinking	[11, 99, 113, 114, 125]	P2, P3, P6, P7, P9, P10, P11	"System understanding, looking at the system, what are the influencing factors, where are the system boundaries, such things, I think, are extremely important." [P2] "You need to be able to question processes and understand what the processes actually do." [P10]
(AI) Problem Solving	[11, 12, 99, 113, 336]	P1, P3, P4, P5, P8, P10	"Typical analytical thinking and structuring is definitely something you would expect." [P3] "You have to stay focused [...] always looking at where the added value is, what you want, which problem you actually want to solve?" [P5]
AI Reflection	[11, 99, 329, 336]	P1, P6, P8	"Unfortunately, you often see models that were used for task A suddenly being used for task B." [P1] "If you can translate the model into the language of the engineer [...] then you've won." [P6]
Social Competencies			
Interdisciplinary Communication and Cooperation	[11, 12, 99, 113, 114, 329, 336]	P1, P2, P3, P6, P8, P10	"They shouldn't just be the super nerd, but should bring some social skills, in the sense of working with other people." [P2] "you have to be able to talk to all stakeholders" [P10]
Change Management	[11, 336]	P1, P7, P9, P10	"The digital transformation towards data science [...] it is not a technical topic, it's a personal and competency-relevant topic. You have to bring people along." [P1] "Huge transformation change topic, so I think [...] listen, listen, talk, listen, talk and then build trust." [P10]

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Category	Supporting Literature	Supporting Interviews	Interview Quotes
Leadership and Decision Making	[11, 12, 113]	P1, P7	"It's less about the technology, but more about the organizational skills to bring something new." [P1] "What does it bring, what does it need, what does it require in terms of staff, capacity, competencies, and what risks do we face?" [P7]
Self-Competencies			
Learning and Curiosity	[99, 113, 114, 125]	P1, P3, P5, P10	"Able to learn, so also knowing that when you come out of university, especially in this field, you still have a lot to learn" [P3]; "The first competency is actually asking the right wrong questions." [P1]
Creativity and Innovation	[113, 114, 125, 336]	P2, P10, P11	"And then I actually have to think out of the box and not just marginally change today's system here and there, but I actually have to rethink the system completely." [P2] "You need the ability to experiment. [...] try things out, keep an overview, and then come to the result." [P11]

Professional Competencies

Data and AI Knowledge As a central point, several authors emphasized the handling and analysis of data, such as data analytics and data science [1, 11, 12, 99, 114, 329, 336]. In addition, some authors explicitly mentioned the understanding of AI technologies, in particular ML [11, 12, 114, 329]. Emphasis is placed on understanding the mathematical foundations, such as statistical knowledge, as well as the benefits and limitations of models [12, 114]. Understanding and using currently available tools and libraries was also mentioned [12].

Ten out of eleven interviewees mentioned the handling and understanding of data and AI. In particular, they referred to preprocessing, structuring, and merging data from different systems, as well as assessing data quality. For ML and AI, experts pointed to the ability to build and use models. This included understanding different types of models and their benefits and limitations. In addition, a few participants noted the value of having a "building kit" of tools for different use cases and data types. Understanding the mathematical underpinnings of ML and model parameters was mentioned.

Overall, this cluster can be characterized as the handling and understanding of the fundamentals of data and AI technologies, as well as the ability to apply tools and models to analyze them.

IT Competencies In the context of Information Technology (IT) competencies, an understanding of digital tools and technologies as well as the basics of computer science were found to be important in the literature [1, 11, 99, 113, 114, 329]. More specifically, several contributions pointed to fluency in programming languages, design patterns, platforms, frameworks and libraries, along with an understanding of software engineering [11, 12, 113, 114, 336].

IT competencies were mentioned throughout the expert interviews. The majority of participants emphasized the importance of understanding software engineering, application development of intelligent functionality, and how AI as a building block interacts with other code elements. In addition, some participants focused on user-centered (application) development and agile software development.

Overall, this cluster describes the competencies of designing, building and programming applications (with intelligent functionalities) and the ability to deal with related frameworks and platforms.

Interdisciplinary Domain Know-How Another common theme in the literature was the integration of interdisciplinary skills and knowledge [1, 12, 99, 113]. Accordingly, several authors put the emphasis on having a foundation in a core engineering discipline, especially when AI is integrated with a physical interface or hardware such as a robot [11, 113, 114, 329].

The majority of participants agreed on the importance of understanding the domain, especially the underlying business and technical processes, and the engineering fundamentals. One interviewee called it the most important skill, as the value of AI only comes from the combination of data science and domain expertise. Participant 1 stated *"as long as we have not built up an understanding of the model, we are very likely to fail with the solution approaches."* [P1].

This cluster can be defined as understanding the technical foundations, physical components, and technical and business processes in the application domain.

Methodological Competencies

Process- and Systems Thinking Another group of competencies highlighted by the literature were process and systems competencies, especially for processes controlled or enhanced by AI [11, 113]. More generally, two papers mentioned systems thinking [99, 114] and Huang et al. [125] added logical and abstract thinking as high-level competencies.

Practitioners also emphasized the importance of understanding and contextualizing business and technical processes, such as the ability to analyze, structure, and deconstruct processes and systems. In addition, about half of the respondents mentioned systems and process thinking in terms of understanding the constraints in the domain, the drivers of the process, and the data that can be used to optimize it.

In summary, this cluster is characterized by structuring, analyzing, describing, modeling, and optimizing (AI) processes and systems.

(AI) Problem Solving Several studies mentioned problem solving competencies [11, 12, 99, 113, 336]. More generally in this category, Huang et al. [125] endorsed observation and analytical skills, while Gottburgsen et al. [99] emphasized the ability to deal with complexity.

Similarly, the competencies mentioned by the interviewees focused on understanding problems and solving them with AI. In addition to the importance of understanding and working from a real, defined problem in a business context, participants emphasized the importance of having an idea of the boundary conditions, tools, and data available to decide if value can be added by using AI.

Overall, this cluster is defined as recognizing and dealing with complex problems and situations and having solution strategies for them (which may involve AI).

AI Reflection From an engineering perspective, the literature highlighted the importance of assessing the technology and its social, legal, and ethical impacts on development [11, 99, 329], judgment [336] as well as responsible action and the ability to reflect on the effects of one's own actions [11, 99, 329]. Accordingly, the ability to judge, reason, analyze, and draw conclusions was mentioned [125]. AI reflection was supported by knowledge of (digital) ethics and an understanding of the legal basis and norms, such as data protection [99, 329, 336].

An important cluster in the interviews was the understanding of the impact of the use of AI in the application context and the assessment of the usefulness of AI in this context. In addition, two interviewees explicitly mentioned the ability to develop explainable AI models to enable the translation of AI models into understandable user language and to gain trust in the model's decisions.

This cluster is summarized as reflecting on the implications of AI technologies, for example in terms of ethical, legal, security and social aspects, and understanding one's own role in this.

Social Competencies

Interdisciplinary Communication and Cooperation In the literature, the ability to communicate, cooperate, and work in teams with people from different disciplines, cultures, and levels of experience was mentioned [11, 12, 99, 113, 114, 329, 336]. In addition to communication and cooperation between different stakeholders, two papers also highlighted the importance of explaining AI behavior to different user groups [113, 329]. Furthermore, competencies for dialog, conflict management and digital collaboration fall under this category [336]. The basis for interdisciplinary communication and cooperation was described by the ability to adapt communication and working styles [11, 114, 336].

These competencies were also mentioned by half of the interviewees. Participants emphasized adaptive communication and cooperation with different target groups, as work on AI systems happens usually at the intersection of multiple departments. Furthermore, the communication aspect was seen as very important to gain acceptance from the end user and to understand the requirements of different stakeholders.

Overall, this cluster describes the ability to communicate and collaborate in an interdisciplinary team environment or with people from different cultures and experience levels, as well as the ability to adapt one's communication and working style to the environment and team.

Change Management Winde & Klier [336] stated the development of strategies to implement change, especially with regard to group dynamics, group cultures, networks and systems. Similarly, André & Bauer [11] mentioned communicating the potential and limitations of AI and supporting the change process by removing fears and coordinating the expectations of different stakeholders.

Managing the change was also mentioned in four interviews. For example, one participant emphasized that working on AI is a *"personal and skills-related issue. You have to bring people along."* [P1]. Similarly, one participant explained the challenge of facilitating the change process: *"[...] then there are other issues like [the fear of] 'I'll be rationalized away' [...] and then you have to fight even more against concerns and communicate and explain what the goal is and point out the benefits."* [P10]. Participants explained that integrating AI into systems and processes requires a transformation of existing processes and sometimes even culture, which makes it necessary to manage the change process in addition to the technological process.

In summary, this cluster summarizes the management and design of change processes, supported by the ability to communicate value, listen, and address fears.

Leadership and Decision Making In the literature, the ability to organize, coordinate and lead teams and the ability to make decisions within the limits of current responsibilities were mentioned [11, 12, 113].

The aspect of leadership, coordination was mentioned in only two interviews. Along the line of how important coordination is, one participant emphasized *"It's less about the technology, but more about the organizational skills to bring something new."* [P1]. Similarly, another participant stressed the need to define *"What does it bring, what does it need, what does it require in terms of staff, capacity, competency, and what risks do we face?"* [P7]

Overall, this cluster is characterized by the ability to organize, coordinate, and lead teams, and the ability to make decisions within the boundaries of current responsibilities.

Self-Competencies

Learning and Curiosity In the literature, the ability to learn and independently acquire contextual knowledge has been highlighted [99, 113, 114, 125]. Furthermore, André & Bauer [11] emphasized the curiosity and willingness to learn how to work with ML and AI systems. In this context, two studies stressed the need for openness to new experiences and technologies in the changing world [114, 329]. In addition, Winde et al. [336] promoted digital learning, such as processing digital information from different sources and using learning management systems.

Accordingly, four interviews also touched on the importance of self-learning and lifelong learning, especially in the context of the fast-moving field of AI. For example, one participant emphasized that it is important to be *"able to learn, so also to know that when you come out of university, especially in this field, you still have a lot to learn"* [P3]. Participants also mentioned the ability to know where and how to get help and to keep up with current technological developments.

In summary, this cluster describes the ability to individually acquire contextual knowledge from multiple sources and the interest, curiosity, and openness to learning new topics.

Creativity and Innovation Several studies expressed the importance of creativity and innovation skills, such as developing novel ideas and improvements by challenging the "status quo" and thinking critically [113, 114, 125, 336]. From a company perspective, this also requires a failure culture [329].

This was also mentioned in three interviews, where the willingness to experiment systematically, the resilience to failure, the patience and drive to find solutions to complex problems, and the ability to think outside the box were mentioned. Challenging existing processes was also mentioned. One interviewee explicitly mentioned the difficulty for engineers to *"think outside of existing control loops"* [P10].

Overall, this cluster is summarized as developing novel, innovative solutions and challenging the "status quo" of processes and ideas.

4.3.2 Study 2: Validated Competency Statements

To further contextualize and validate the identified clusters, this part of the study developed and validated competency statements derived from the identified clusters.

Content Validity

As a first step, an initial set of competency statements was derived based on the identified competency clusters and aspects mentioned in the literature and interviews. The item set is presented in Appendix A.2. These were rated by 32 experts (Table 4.2) for relevance and clarity. The experts were also able to suggest improvements for each cluster. The resulting analysis of relevance and clarity, as well as the decision, is reported in Table 4.4.

Table 4.4: Individual content validity per competency statement for relevance and clarity reporting the mean, the standard deviation (SD), the content validity index (CVI) (proportion of experts signaling agreement through votes 3 and 4), and the final decision. Relevance was assessed on a Likert scale of *1 - not relevant, 2 - somewhat relevant, 3 - quite relevant*, and *4 - very relevant*. Clarity was rated as *1 - not clear, 2 - item needs some revision, 3 - clear but needs minor revision*, and *4 - very clear*.

ID	Item	Relevance			Clarity			Decision
		Mean	*SD*	*CVI*	*Mean*	*SD*	*CVI*	
1	Understand fundamental concepts of data science and AI	3.56	0.67	0.91	3.38	0.83	0.84	No change
2	Select and utilize appropriate AI tools for different use cases and data types	3.34	0.65	0.91	3.50	0.62	0.94	Adapted
3	Build and evaluate AI models	3.00	0.92	0.72	3.38	0.83	0.84	Adapted

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Table 4.4 – continued from previous page

ID	Item	Relevance			Clarity			Decision
		Mean	*SD*	*CVI*	*Mean*	*SD*	*CVI*	
4	Design and program applications with AI functionalities using relevant languages and frameworks	3.09	0.82	0.78	3.28	0.81	0.78	No change
5	Work with various AI frameworks and platforms	2.84	0.88	0.66	3.63	0.49	1.00	Exclude
6	Integrate AI components into existing IT infrastructure	2.94	0.91	0.75	3.50	0.76	0.91	Exclude
7	Understand the technical foundations of the application domain	3.59	0.67	0.91	3.50	0.80	0.88	No change
8	Understand technical and business processes in the application domain	3.06	0.84	0.75	3.38	0.91	0.84	Adapted
9	Implement AI solutions to domain-specific technical and business processes	3.09	0.78	0.81	3.56	0.67	0.97	No change
10	Structure, analyze and break down systems and processes	3.53	0.67	0.91	3.59	0.67	0.91	No change
11	Identify data-driven optimization opportunities	3.31	0.74	0.84	3.44	0.80	0.88	No change
12	Analyze and improve AI-enhanced processes	3.03	0.82	0.81	3.31	0.78	0.88	No change
13	Identify and define real-world problems suitable for AI solutions	3.72	0.58	0.94	3.69	0.64	0.91	No change
14	Assess available tools, data, and constraints for AI problem-solving	3.38	0.66	0.91	3.59	0.76	0.91	No change
15	Develop and implement AI strategies to address complex issues	3.03	0.86	0.78	3.38	0.91	0.78	Adapted
16	Assess the social, legal, environmental and ethical implications of AI technologies	3.09	0.89	0.72	3.50	0.88	0.81	No change
17	Assess usefulness of AI in an application context	3.34	0.87	0.81	3.41	0.91	0.84	No change
18	Reflect on personal responsibility and professional ethics in AI	3.03	0.93	0.59	3.59	0.71	0.88	Adapted
19	Communicate AI concepts and behavior to diverse stakeholders	3.34	0.83	0.84	3.50	0.72	0.94	No change
20	Collaborate in multi-disciplinary project teams	3.72	0.52	0.97	3.75	0.44	1.00	No change
21	Adapt communication style to different stakeholders	3.28	0.77	0.81	3.56	0.62	0.94	No change
22	Manage and shape change processes considering organizational dynamics	2.69	0.97	0.59	3.03	1.12	0.72	Exclude
23	Address concerns and resistance to AI adoption	2.78	0.83	0.59	3.28	0.92	0.81	Exclude
24	Inspire change by communicating AI value and potential	2.72	0.89	0.56	3.44	0.91	0.78	Exclude
25	Organize and coordinate diverse AI project teams effectively	3.00	1.05	0.78	3.53	0.80	0.94	Adapted
26	Make strategic decisions regarding AI implementation	2.97	1.06	0.75	3.47	0.80	0.94	Exclude
27	Align AI initiatives with organizational goals	2.78	1.07	0.63	3.41	0.95	0.81	Exclude
28	Acquire and apply new AI knowledge independently	3.19	0.82	0.81	3.50	0.88	0.88	No change
29	Curiosity and openness to learn new topics	3.59	0.67	0.91	3.69	0.64	0.91	No change
30	Research and gather information from various sources	3.53	0.62	0.94	3.63	0.75	0.91	No change

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Table 4.4 – continued from previous page

ID	Item	Relevance			Clarity			Decision
		Mean	*SD*	*CVI*	*Mean*	*SD*	*CVI*	
31	Questioning the status quo of existing processes	3.41	0.71	0.88	3.66	0.60	0.94	No change
32	Re-imagine processes and systems with AI integration	3.22	0.79	0.84	3.63	0.61	0.94	No change
33	Experiment systematically with AI-based solutions	3.25	0.80	0.84	3.53	0.76	0.91	No change
	Average over all items	3.20	0.80	0.80	3.49	0.77	0.88	

Open Comments

Regarding the *data and AI knowledge* items (items 1-3), experts questioned the wording of certain items, for example, what falls under “fundamental” or “appropriate”. There was also a suggestion to separate building AI models from evaluating them. As one expert suggested: *“Breaking up building and evaluating AI models is also necessary. Most engineers will not need to build an AI model, but almost all will implicitly evaluate an AI model when using it.” [Expert 28].*

In the *practical competencies* (items 4-6), opinions varied mostly in the context of establishing an understanding of the respective role. One expert emphasized *“Obviously, for a small group of specialists who are engaged in developing AI application software, being able to build AI models into software would be important. However, for other engineers this is irrelevant.” [Expert 19].* Similarly, another expert commented that *“These are slightly different competencies and the required knowledge of each will depend on the role the person is playing.” [Expert 18].*

For the items of *interdisciplinary domain knowledge* (items 7-9), experts suggested adding more clarity to the technical and business processes (item 8), but also underlined the importance: *“Understanding the domain is extremely important to engineers and some level of business knowledge and processes is also required.” [Expert 17].* Similarly, Expert 28 mentioned: *“Good selections and scope here - again, implementation of an AI solution may not be an every engineer thing, but use of a domain-specific AI solution certainly is.”.*

Regarding *process and systems thinking* (items 10-12), it was mentioned *“Very important. Not all processes will be suitable for AI, at some processes humans will remain superior” [Expert 11].* This was also mentioned along the lines of *(AI) problem solving* (items 13-15), with one expert stating *“The first point is the most relevant. We don’t need to ’AI-Everything’ we have great working solutions in some fields.” [Expert 10].*

The items of *AI reflection* (items 16-18) were highlighted as important: *"This set is probably the most important set of questions as all engineers of all disciplines and work contexts will need to consider these."[Expert 28].*

Interdisciplinary communication and collaboration (items 19-21) was discussed in relation to the role of an engineer in communicating with management. Similarly, the items in the *Change Management* cluster (items 22-24) were critically evaluated. Here it was suggested to *"consider adding an element of communicating risks and potential unintended consequences of AI adoption in context." [Expert 28].* Similarly, *Leadership and decision making* (items 25-27) were also not seen as a core engineering task, with one expert stating *"Organizational goals might be too high level. AI improves less downstream processes" [Expert 11]*, while another expert suggested that this was not AI-specific: *"students [should] do this regardless of whether it is an AI project team." [Expert 20].* The same expert also mentioned the non-AI specificity in the cluster of *learning and curiosity* (items 28-30). Regarding creativity (items 31-33), one expert emphasized that *"A bad process remains a bad process, even with AI" [Expert 11].*

Adopted Item Set

The quantitative assessment reported in Table 4.4 and the open comments led to the exclusion of seven items, while one new item was created based on suggestions from the experts. In addition, six items were adjusted for clarity based on the experts' suggestions. The overall sample after exclusion had a mean relevance score of 3.28 (Standard Deviation (SD)=0.77) and a S-CVI score of 0.83. Accordingly, the overall clarity was 3.53 (SD=0.75) with an S-CVI score of 0.89. The revised item set is reported in Table 4.5.

4.4 Discussion

In this chapter, domain-specific AI competencies for engineers were conceptualized based on an initial identification of competency clusters from interviews with industry practitioners and literature, as well as a content validity survey with an expert panel. Key findings are discussed below, including limitations of the study, implications, and future directions.

Table 4.5: Adopted item set for domain-specific AI competencies for engineers structured along type, competency area and items. Rephrased items are marked with *.

Type	Competency Area	ID	Item
Professional Competencies	Data and AI Knowledge	C1	Understand fundamental concepts of data science and AI (e.g., maths, data types, etc)
		C2	Select relevant AI tools for different use cases and data types*
		C3	Use and evaluate AI tools for different use cases and data types*
	Practical Competencies	C4	Design and program applications with AI functionalities using relevant languages and frameworks
	Interdisciplinary Domain Know-How	C5	Understand the technical foundations of the application domain
		C6	Understanding the technical and business processes specific to the application domain.*
		C7	Implement AI solutions to domain-specific technical and business processes
Methodological Competencies	Process- and Systems Thinking	C8	Structure, analyze and break down systems and processes
		C9	Identify data-driven optimization opportunities
		C10	Analyze and improve AI-enhanced processes
	(AI) Problem Solving	C11	Identify and define real-world problems suitable for AI solutions
		C12	Assess available tools, data, and constraints for AI problem-solving
		C13	Solve complex problems using AI tools*
	AI Reflection	C14	Assess the social, legal, environmental, and ethical implications of AI technologies
		C15	Assess usefulness of AI in an application context
		C16	Reflect on personal responsibility and uphold professional ethics in the development and deployment of AI technologies*
Social Competencies	Interdisciplinary Communication and Cooperation	C17	Communicate AI concepts and behavior to diverse stakeholders
		C18	Collaborate in multi-disciplinary project teams
		C19	Adapt communication style to different stakeholders
		C20	Communicate risks and potential unintended consequences of AI adoption*
		C21	Collaborate on AI projects in project teams*
Self-Competencies	Learning and Curiosity	C22	Acquire and apply new AI knowledge independently
		C23	Curiosity and openness to learn new topics
		C24	Research and gather information from various sources
	Creativity	C25	Questioning the status quo of existing processes
		C26	Re-imagine processes and systems with AI integration
		C27	Experiment systematically with AI-based solutions

4.4.1 Main Findings

What professional, methodological, social, and self-competencies do engineering students need to work with AI systems?

This chapter addressed RQ 1 of *what professional, methodological, social, and self-competencies do engineering students need to work with AI systems?* Following the argument for a domain-specific perspective on AI competencies [153, 255], it provided a basis for defining competency profiles for different roles in the context of AI and engineering.

In the context of *professional competencies*, the clusters of data and AI knowledge, practical competencies, and interdisciplinary domain know-how were identified. These cover the understanding of fundamental concepts of data science and AI, as well as the selection, use and evaluation of relevant AI tools. They also include the design and programming of applications that incorporate AI functionalities, as well as the understanding of technical fundamentals, technical and business processes to adapt AI solutions to the application domain.

The *methodological competencies* highlight structure around process and systems thinking, (AI) problem solving, and AI reflection. Process and systems thinking emphasizes analyzing systems, identifying optimization opportunities, and improving AI processes, while (AI) problem solving involves defining problems suitable for AI, evaluating tools and constraints, and solving complex problems using AI. In addition, the AI reflection competency area focuses on assessing the broader implications of AI technologies and personal responsibility in their use.

The *social competencies* focus on interdisciplinary communication and collaboration and include, for example, communicating AI concepts to various stakeholders, working in teams, and adapting communication styles. Finally, the *self-competencies* identified were learning and curiosity, and creativity. Learning and curiosity involves independent learning, curiosity, and information gathering, while creativity encourages questioning existing processes and experimenting with AI solutions.

Overall, the identified competency profile highlights a holistic view of AI competencies in the engineering domain, encompassing technical, methodological, social, and self-competencies. It connects to the call for a domain-specific conceptualization of competency profiles [153, 255] and provides a foundation for further research efforts.

Secondary Findings

Beyond the main findings, there are three secondary findings on related aspects.

Transversal Competencies Notably, in the validation step, most items were excluded from the competency areas of change management, leadership, and decision making, with expert comments suggesting that these are not necessarily seen as core engineering responsibilities. This is consistent with the discourse on transversal competencies in engineering education, which often places more emphasis on teaching technical competencies that are more familiar to educators and neglects transversal competencies that are more difficult to teach and assess [178].

Conceptualizing AI Competencies Comments from experts in the survey also reflect the current discourse on AI competencies, whether they stand alone or permeate existing competencies such as learning and curiosity or leadership. As discussed in Section 3.2, it can be argued that digital technologies permeate existing cultural techniques, and therefore separate teaching and learning of digital competencies is not meaningful [147]. In the context of future skills, Kalz [140] argued for a link to previous competency models rather than creating new lists of competencies, the selection and prioritization of which would have to be newly justified. Similarly, Mikeladze, Meijer and Verhoeff [216] argued that AI competencies follow as a progression from digital competencies. At the same time, as with digital literacy, the question arises whether AI competencies are actually a plurality of skills that can only be taught and learned if they are anchored in the subject [146]. This supports the conceptualization of domain-specific AI competencies that contextualize the use of AI in a particular domain, as highlighted in recent reviews on AI competencies [153, 216, 255]. However, it also demonstrates the ongoing discourse on what AI competencies entail [8, 177] and to what extent they are a set of separate competencies or need to be anchored in a domain context.

Role-based Conceptualization Comments in the expert panel also emphasized that certain competencies depend on a particular role or are easier to conceptualize and assess in the context of roles. Such a role-based approach, although new to engineering, has been widely accepted in another professional field - medical education. The approach has been applied both to roles in the profession for which students need to be prepared and to better understand the roles of faculty as educators. For example, Harden and Crosby [110] argued that given the changing and complex role of teaching in medical education, it is important to categorize these roles so that teachers or educators can identify what kind of expertise they need in the medical field and in their roles as teachers. Whitehead et al. [328] further emphasized that although more work needs to be done, the use of roles to describe competencies and build competency-based frameworks is now the norm in medical education, reflecting “a conceptual shift in understandings of medical education from a process representing one of knowledge acquisition and time-based clinical rotations to one in which competence can be considered as the adequate performance of a set of professional roles” [328, p. 786]. Thus, a role-based approach could add detail and make it easier to anchor the conceptualization of domain-specific AI competencies.

4.4.2 Limitations

The significance of our findings is limited by three factors. First, because the interdisciplinary role of AI in engineering is not yet fully established, different forms can be found in companies or in the literature. Depending on the envisioned role, different competencies may be given different importance. In study 1, this limitation was addressed by selecting interview partners and literature from different perspectives, such as literature on competencies for engineering in Industry 4.0 and AI literacy competencies. In addition, the content validity study (study 2) provided further validation of the competencies through a diverse expert panel.

Second, the sample of experts and engineering practitioners addressed in the interviews and validation study may not be representative or may be influenced by non-random selection of participants. Thus, the internal validity is threatened by selection bias. In addition, the findings are context dependent and may not generalize to other fields or locations. To mitigate the potential threat to validity, the selection of participants was diverse and broad across different roles and disciplines, with an emphasis on cross-validation across different engineering disciplines. In addition, the sample and context were documented and reported to allow for contextualization of the findings. Finally, the interviews followed a structured interview protocol and were not open-ended, so they could be replicated in other settings.

Third, the definition of competency in AI is ongoing and dynamic. This has been acknowledged in several reviews [177, 216, 255]. As AI technologies change, so will work practices and related competencies. Thus, the identified competency profile may evolve in the light of technological developments over the coming years.

4.4.3 Implications and Future Directions

Overall, this chapter has provided a first domain-specific conceptualization of AI competencies for engineering education, following calls for a bottom-up approach to competencies [8] and anchoring AI competencies in the disciplines [146, 153, 255]. There are three main implications and future directions that can be drawn from this work.

Basis for Operationalization

First, the identified competency profile can serve as a reference for competency-oriented study development and curriculum design for people who are learning these competencies from scratch or for people who want to upgrade their skills. Thus, it can be operationalized in study programs or inform the learning outcomes of courses.

The competency profile also emphasizes the importance of methodological, social and self-competencies alongside the professional competencies, and underlines the need to strengthen and integrate these aspects in the curricula of study programs and possibly even technical subjects. This is in line with the trend to emphasize interdisciplinary and transversal competences in engineering education [178, 312]. An example of operationalization could be interdisciplinary and transversal projects or the integration of topics from different industries in engineering curricula. A future direction could be the establishment of an overarching learning catalog that includes AI-related competencies within specific domains and roles, integrating existing frameworks such as the European Skills/Competencies, Qualifications and Occupations (ESCO) [70] or other competency frameworks for AI in various domains [255].

Foundation for Scale Development

The competency profile is also a first step towards the creation of a domain-specific assessment tool, as proposed by Knoth et al. [153]. As discussed in Section 3.2.6, assessment instruments currently focus on generic AI competencies rather than domain-specific AI competencies. Thus, the development of assessment tools for domain-specific AI competencies would further support the assessment of individuals' AI competencies in their professional domain and beyond, as well as allow for the building of evidence for educational interventions [177]. Building on the work of this chapter, such an endeavor would require further definition of a targeted intervention scenario and construct validity with a target sample of engineers or engineering students [28, 205].

Role-Based Approach

As highlighted in the comments on the content validity study, it is often difficult to contextualize a broad conceptualization of competencies within one's discipline or role. To address this, another direction could be to adopt a role-based approach to AI competencies, as suggested in [pub:17]. In summary, a role-based approach makes it easier for those new to a topic or domain to approach it and have a guide or mental model of what it looks like, including responsibilities and goals. It creates group-level constructs, meaning that roles define or identify groups of professionals who are "guided in their domain of practice by an established set of heuristics for thought and action" [209, p. 4]. The encapsulation of knowledge as a role makes it task-based and thus easier for a newcomer to grasp because of its alignment with practice.

Professionals who perform a particular role require a specific set of knowledge or expertise. The knowledge required to perform a given role is known as "role knowledge" [209, p. 12]. This approach can also be used to examine the roles that professionals may play in the workplace in relation to AI, and what this means for what students need to be taught to prepare them for the workforce. This idea has been conceptualized with examples from engineering education in a recent paper [pub:17].

4.5 Summary

Located in the research context of AI competencies, this chapter proposes a conceptualization of domain-specific AI competencies for engineers based on interviews with industry practitioners, literature, and a validity study with an expert panel. By addressing the current challenges of lack of consensus and linking to other competency profiles (see Section 3.2), it takes a domain-specific approach to AI competencies with a focus on the application domain of engineering. Thus, the chapter contributed to the question of *how to conceptualize domain-specific AI competencies in the application domain of engineering*, and in particular *what professional, methodological, social, and self-competencies engineering students need to work with AI systems.*

The conceptualization of domain-specific AI competencies for engineering provides a foundation for further research efforts, but also for practical operationalization in programs and courses. This operationalization will be addressed in the following two chapters, first at the program level (Chapter 5) and then at the course level (Chapter 6).

5

Developing and Validating an Interdisciplinary Curriculum for AI in Engineering

The previous chapter demonstrated that the integration of AI tools and methods into the engineering domain has become increasingly important, and with it a shift in the required competencies. As a result, engineering education faces the challenge of integrating AI competencies into its courses and curricula. While interdisciplinary education at the subject level has been explored [312], the development of interdisciplinary curricula is often challenging.

This chapter presents the use of the *Curriculum Workshop (CW) approach* to develop an interdisciplinary, competency-based curriculum at the intersection of AI and engineering. Using a case study of a newly developed interdisciplinary Bachelor's program in AI in Engineering, the chapter evaluates the curriculum workshop approach as a development mechanism and discusses various aspects of its implementation through self-evaluation procedures and surveys of workshop participants. Furthermore, the results of the development are assessed through formative evaluation using a curriculum mapping approach and focus group interviews with experts.

The chapter builds on the published work of [pub:1, pub:9, pub:23] and one work [pub:22] under review. The results show that the structure and competency orientation of the method facilitate the alignment of participants from different disciplinary backgrounds. Moreover, the formative evaluation of the curriculum demonstrates its expected effectiveness and practicality.

Overall, interdisciplinary curriculum development needs to take into account different perspectives and demands on the curriculum, which increases complexity and requires a more structured design process. The findings highlight the importance of interdisciplinary curriculum design in engineering education and provide practical insights into creating competency-based curricula with the curriculum workshops approach. The results also provide a reference curriculum that operationalizes the identified competency profile and can serve as a reference for further curriculum innovation and scholarship.

5.1 Research Context

Contextualizing Programs This chapter focuses on programs, particularly the content side of curriculum development. As shown in Figure 5.1, program and curriculum development is influenced by technological developments and pedagogical models at the supra level, but must also adhere to national standards and laws. In addition, curricular decisions often respond to societal and industry needs. As programs are located in institutions, they must also follow institutional standards, and development is shaped by the participating educators and their knowledge and beliefs about education, as well as their experiences and identities. On the other hand, programs and curricula inform courses and the particular learning outcomes that should be taught.

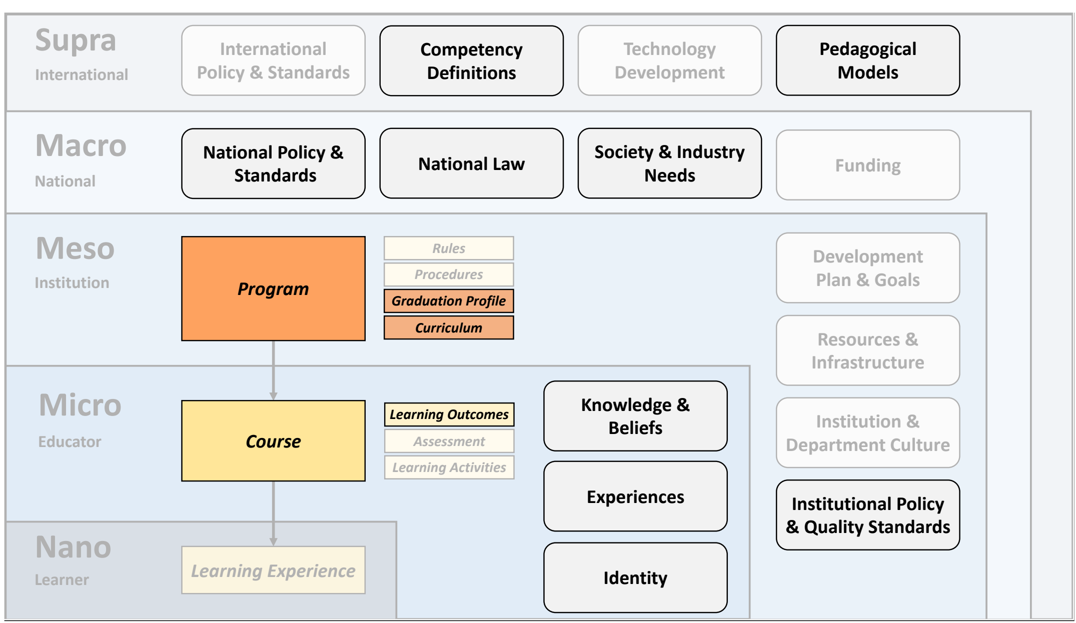

Figure 5.1: Programs in the system model of influences. The visible light-gray boxes indicate relevant influence factors that influence programs or which are informed by them.

Need for Program Development Research in Engineering Education As discussed in Section 3.1, the rapid advances in AI have also begun to impact engineering practices [107, 135, 228]. AI impacts engineering education from two perspectives. On the one hand, the use of AI tools in education can open up new teaching and learning methodologies [31, 136]. On the other hand, the use of AI tools in an engineering context creates new professional roles and required competencies at the intersection of AI and engineering, making it necessary to integrate these topics into engineering curricula and pedagogy [198]. This is also supported by a recent study on the impact of generative AI on higher education, which highlights the push towards interdisciplinary teaching and the need for interdisciplinary curriculum frameworks [57].

Although computing and computing education have already become an integral part of the engineering profession and engineering education, and topics such as programming, data analytics, and computational science are now commonly taught in engineering curricula [202, 261], there is limited experience and systematic evidence on teaching AI in an engineering context. As highlighted in Section 3.3, engineering educators have integrated AI education into individual lectures, courses, or projects [130, 233, 284]. In addition, the need to develop AI competencies across disciplines is recognized [153, 255]. At the same time, the integration of AI education at the curricular level or the development of a full interdisciplinary program of study in higher education has not received much attention. Consequently, the understanding of how to develop and implement such novel and interdisciplinary curricula is still limited. While Chapter 4 addressed the domain-specific AI competencies, this chapter focuses on their operationalization in curricular structures.

In the context of this chapter, a curriculum is referred to as the overall plan of modules and student experiences in an educational program, following the brief definition of Taba [296] as a "plan for learning". While a program includes the structural, organizational, and legal framework of a program, curriculum in this context focuses on the normative basis of content learning objectives, learning activities, and assessments. Thus, a curriculum is more than a compilation of discrete subjects, but design an overarching framework for the development of an academically trained personality. Here, an interdisciplinary curriculum is often expected to address knowledge and skills that address students' real-world problem-solving competencies [312].

Interdisciplinary curriculum design is a complex task that poses several challenges. One challenge is determining the order in which students learn content, either going deeper in a single discipline or first understanding the breadth of the field [14].

In addition, designing an interdisciplinary curriculum requires finding agreement between different disciplinary cultures, experiences, and interests [219]. It involves finding common ground and mutual understanding. Overall, interdisciplinary curriculum development is a difficult task, but can be key to bringing new perspectives and competencies to engineering education [312]. As engineering education continues to evolve to meet the changing needs of industry and research, it is necessary to understand the practical aspect of interdisciplinary curriculum development to include a novel set of AI competencies or to create novel curriculum approaches.

Contributions and Research Questions This chapter aims to deepen the understanding of interdisciplinary AI curriculum development by presenting and analyzing a case study focused on an undergraduate program that integrates AI and engineering. Specifically, it explores how to translate an interdisciplinary competency profile for applying AI in engineering (as discussed in Chapter 4) into a coherent interdisciplinary curriculum.

The central question of this chapter is *how to develop and evaluate an interdisciplinary AI curriculum.* To answer this question, the chapter takes both a process-oriented and an outcome-oriented perspective.

First, the development process of such novel interdisciplinary programs is established through an adaptation of the curriculum workshop method. Then, its effectiveness in developing an interdisciplinary curriculum is evaluated within the case study. Key aspects analyzed include interdisciplinarity, collaboration, participation, and composition, as well as key considerations in implementing the curriculum workshop method in an interdisciplinary setting.

To explore the process aspects, the chapter addresses the following sub-questions:

- *RQ 2.1: How do participants evaluate the effectiveness of the curriculum workshop method in developing an interdisciplinary curriculum at the intersection of AI and engineering?*
- *RQ 2.2: What factors do participants identify as influencing successful collaboration during interdisciplinary curriculum development workshops?*

Second, the quality and consistency of the developed curriculum is assessed through a curriculum mapping that aligns the intended competency profile with the corresponding courses. In addition, a qualitative view of the perceived consistency, practicality, and effectiveness of the curriculum from an educator and industry perspective is provided.

In evaluating the results of curriculum development, the following questions are addressed:

- *RQ 2.3: How well does the developed curriculum align with the identified competency profile?*
- *RQ 2.4: How do perceptions of the developed curriculum differ between industry representatives, participating educators, and non-participating educators?*

Overall, the findings highlight how an interdisciplinary curriculum can be developed using a curriculum workshop approach and provide a practical understanding of the development outcomes. In addition, the development outcomes provide a reference curriculum for AI and engineering for further development at other institutions or accreditation standards.

Chapter Outline The remainder of the chapter is organized as follows: Section 5.2 focuses on the underlying methodology, including the research approach that provides the context for the case study and the assessment instruments. Next, Section 5.3 examines the results of the evaluation of the development process. Section 5.4 presents the results of the curriculum mapping and the qualitative findings from the focus group interviews. The results are discussed and contextualized in Section 5.5. Section 5.6 summarizes the main findings and provides an outlook for future work.

5.2 Methods and Materials

An overview of the research design is given in Figure 5.2 addressing two main aspects: the process and the formative evaluation of the development outcome. On the process side (study 1), the curriculum workshop, which refers to a series of workshop sessions with all stakeholders from the participating disciplines, was developed based on existing approaches to curriculum development from the literature (see Section 2.2). This theoretical artifact was tested in practice with a case study of a curriculum workshop series for an interdisciplinary Bachelor program at the intersection of AI and engineering. The development process was evaluated through self-evaluation procedures of the facilitators and quantitative ex-post surveys of the participants at the end of the workshop series.

In the formative evaluation of outcomes (study 2), the development outcomes were evaluated through focus group interviews and curriculum mapping (see Section 2.2.3). The following part first contextualizes the case study, describing the theoretical artifact as well as the implementation of the process and the results of it.

In addition, the evaluation tools of the development process are described following Figure 5.2.

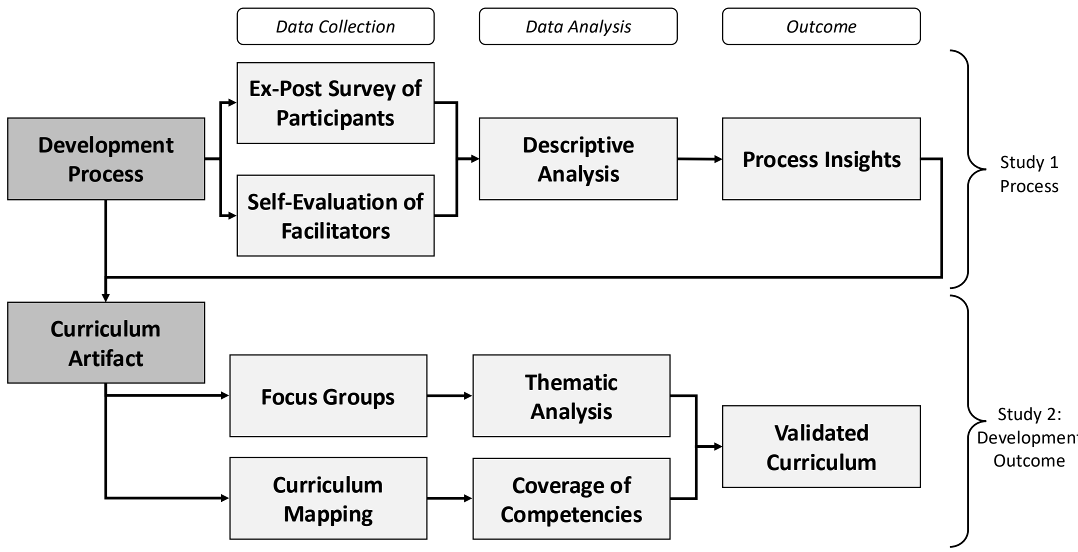

Figure 5.2: Research design overview for curriculum development evaluation including two steps on focusing on the process (study 1) and focusing on the outcome of the development (study 2).

5.2.1 Case Study: Development of Bachelor Program AI Engineering

The case study describes the development of the novel Bachelor's degree program "AI Engineering - Artificial Intelligence in Engineering" (hereafter referred to as AI Engineering) with its special structural and content-related features as well as a competency-oriented program development[1]. AI Engineering aims at a new kind of curriculum development that has no reference to existing competency profiles or programs. The interdisciplinary setting at the intersection of AI and engineering involves participants from different domains with different experiences and broad demands on the curriculum. In addition to the strong interdisciplinary orientation of the program at the interface of AI and engineering, special features are the creation, implementation and execution of the program as a cooperation of five universities as well as a project- and industry-oriented focus.

[1] The program has been established as a study program in the winter semester 2023/24 [url:14]. Further information on the organizational aspects of the study program are summarized here [url:10]

The case can be further contextualized in the drivers identified in Section 3.1 and Figure 5.1. As a newly developed curriculum, it follows the rebuild strategy [158] and creates new educational experiences from scratch. The goal of the program and the vision is to bridge the gap between engineering and AI and to train so-called AI engineers who can develop data-driven solutions for engineering use cases. This interdisciplinary competency profile focuses on the ability to work responsibly with data and AI models, as well as having a domain understanding of the underlying engineering processes, data and requirements. It also requires a high level of systematic problem-solving skills and the ability to communicate effectively across disciplines. As a new curriculum, about half of the modules are newly developed to target different educational experiences, such as projects, flipped classrooms, or hackathons. In addition, there is an emphasis on the development and use of OER in the classroom, and on collaboration with industry.

The development of the program has been influenced by several internal and external drivers. On the external side, AI education is currently high on the political agenda and funding has been provided to establish the program. In addition, the content and implementation are shaped by interactions with industry partners. Internally, the program is primarily influenced by the educators who designed the program and secured the funding to establish it. While the need for such a program was recognized at the faculty and institutional level, its development was not top-down or part of strategic initiatives for further development. In addition, the program is only possible in its current form because of the availability of resources, particularly in terms of faculty staffing, which is largely funded by external sources, and existing student computing resources. The culture of the institution and the faculty was initially resistant to change, especially in terms of new approaches to teaching and curriculum structure. At the same time, external funding and government support were perceived as validation of the ideas and acceptance of the proposed curriculum.

This interdisciplinary setting at the intersection of AI and engineering involves participants from multiple domains with different experiences and broad demands on the curriculum. In order to achieve the goal of new development and synthesis of the subject areas, it was necessary to choose a method of curriculum development that involves different disciplines, promotes ideas, and does not depend on existing models and training standards or comparable courses of study (see Section 2.2 for an overview). Therefore, a participatory approach in the form of an adaptation of the curriculum workshop approach [273, 331] was chosen to foster discussion and alignment among all stakeholders. This section describes the participatory curriculum development process using the curriculum workshop approach. This includes insights into the approach of each workshop as well as adaptation processes.

5.2.2 Development Approach: Curriculum Workshop Method

The curriculum workshop method is a participatory method of curriculum development (see Section 2.2). It combines the "goals and demands of a participatory curricular degree program development with various aspects of organizational development" [331, p. 339]. In the context of developing new degree programs, the curriculum workshop can help structure the process and collaborate on the design. It provides a space for direct communication and allows the different actors involved in the process to exchange and get to know each other. [331, p. 343],[102, p. 2], which is particularly relevant in the context of curriculum development of interdisciplinary and novel degree profiles.

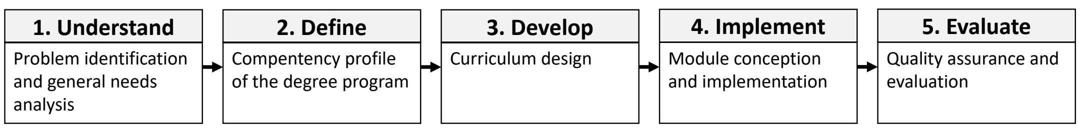

Figure 5.3: Five phases of curriculum development using the curriculum workshop approach.

The model includes five phases relevant to curriculum development (Figure 5.3):

Phase 1: Understand The first phase involves problem identification and a general needs assessment. This includes identifying current problems that the program should address, as well as general needs. Questions addressed in this phase include: How are the topics of the program currently being implemented, what are the requirements and expectations of future graduates, and what are the possible areas of professional activity? Addressing these questions should provide a common basis for further development of the curriculum and highlight key content.

Phase 2: Define In the second phase, the focus is on the graduate profile, identifying what graduates should be able to do at the end of the program and defining the program's overarching learning outcomes and qualification goals. It also determines the thematic focus of the curriculum. The aim of this phase is to develop a competency profile that includes the specific competency objectives of the program.

Phase 3: Develop The third phase focuses on the concrete translation of the insights gained in the previous two phases into a module catalogue. The phases addresses questions such as: How can the program be meaningfully structured into modules based on the competency profile, and what should students be able to do after completing each module? How can the modules build on each other, and what is the appropriate sequence? Overall, the first three phases define the structure of the curriculum.

Phase 4: Implement In the transition from Phase 3 to Phase 4, the actual courses are developed in accordance with the module descriptions. In addition, specific teaching and learning activities, and assessment methods can be defined in terms of Constructive Alignment (Section 2.3). The overall perspective of the program must also be considered. Are all areas of the competency profile represented and meaningfully integrated into the program, and is studyability ensured? This phase is followed by the implementation of the program.

Phase 5: Evaluate The final phase begins with implementation. Appropriate evaluation measures can be used to examine the implementation of the curriculum. For example, surveys of students and faculty can support the evaluation [300]. Insights from the evaluation, especially with regard to accreditation and changing labor market requirements, can lead to a reiteration of individual phases. In this way, the method is integrated into quality management processes and can be seen as a continuous development of programs.

While the curriculum workshop approach can theoretically be applied to any new curriculum development, its implementation is exemplified in the next section with the case study of AI Engineering. Materials and guides are available as a reference for further use [url:13].

5.2.3 Implementation of Development Process in the Case Study

Overview The starting point for the implementation of the curriculum workshops was the creation of a completely new degree program, which is currently being implemented in cooperation with five universities. In each of the phases described above, workshops were planned to implement the process to develop a new curriculum. A total of ten workshops were held in the process of developing the core structure (phases 1-3), which together with the development of the module matrix, form the core of the curriculum. As phases 4 and 5 are part of the initial ongoing implementation and quality assurance of the program, they are not included in the analysis.

The curriculum development took place between February 2022 and July 2022. The participants of the development process were delegated by the participating universities. Figure 5.4 extends the overview concept described in Figure 5.3 with the workshops that were necessary to implement the individual phases in the case study. Each number represents a workshop.

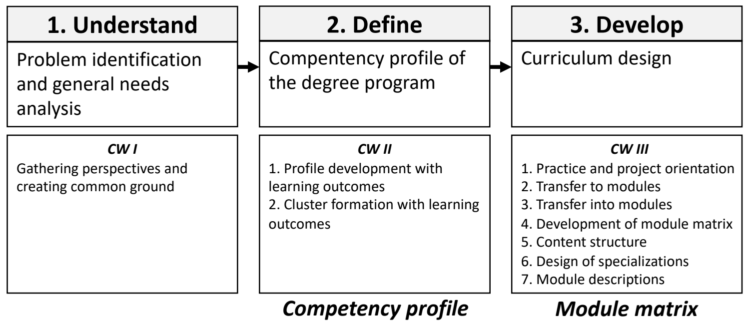

Figure 5.4: Implementation of first three phases curriculum workshop approach with respective workshops per phase.

After the implementation of the first phase *Understand* as part of one CW, the second phase *Define*, which had the competency profile as its goal, was implemented through two CWs. CWII-1 focused on the central question of what skills and competencies graduates should have at the end of their studies. The collaborative development resulted in a clear profile for the program based on two main competency areas. In CWII-2, these areas were revisited and refined, resulting in several clusters that served as the basis for developing the competency profile. This profile was further developed outside the workshops and used in subsequent workshops to design the module matrix in the third phase[2]. In the third phase, *Develop*, in addition to the concrete design of the module matrix, several themes were jointly developed that were important for the development of the individual modules. For example, CWIII-1 focused on the central theme of practice and project orientation, while CWIII-2 and 3 developed possible study plans based on a modular system. This formed the basis of the module matrix, which was further discussed and reviewed in CWIII-4. Finally, in CWIII-5-7 the explicit content was further sharpened and worked out together.

Workshops Each workshop session was led by two facilitators and supported by an impulse presentation. The participants were professors and research assistants who were part of the development project and delegated by the five participating universities. The average number of participants in the workshops was 18, and the dates were set by pre-registration surveys to allow as many people as possible to attend, and to ensure that each university was represented in the workshop sessions.

[2] Parts of the developed competency profile are shown in [pub:12] and further described in Section 5.2.4.

The target group of participants remained the same across the workshops, but the composition of participants changed in some cases over the course of the workshops. Because of the different locations of the universities, the workshops were conducted in an online format.

After an introduction to the content and a short update for the participants, the workshop focused on co-creation in smaller sub-groups on the respective topics. Participants worked online on a visual collaboration platform that allowed for synchronous work and compilation of results. At the end of each session, the results were brought together in the plenum. After each workshop session, the results of the group or individual work were categorized, sorted, and further processed by the facilitators in such a way that, if possible, a new artifact of the development process emerged.

The workshops initially lasted three to four hours. However, experience and feedback from participants indicated that a shorter duration of two hours produced comparable results, so the workshops were shortened in the later phase of the workshop series. Because of changing attendance of the participants, the workshops were prepared in such a way that they could be attended independently of each other. A detailed description of the timing and structure of each workshop, its key questions and specific work assignments can be found in [pub:1]. Additional materials for reuse are available at [url:13].

Interdisciplinarity in the Development Interdisciplinarity in this context describes both a disciplinary collaboration between engineering and AI, as well as between the different engineering disciplines. In order to practice participatory co-creation, the goal was to ensure that at least one representative from each institution and each discipline could participate in in each session. At the same time, participants were free to participate according to their availability, which resulted in an unbalanced number of institutions or disciplines in some workshop sessions. During the development of the competency profile and the module matrix, a concentration of expertise was achieved through small group work according to subject affiliation, which was then brought together and discussed in the large group. The mixing and discussion led to an exchange between the disciplines.

5.2.4 Outcomes of the Development

In order to contextualize the results of the development processes in the case study, the underlying competency profile and curriculum are briefly described below.

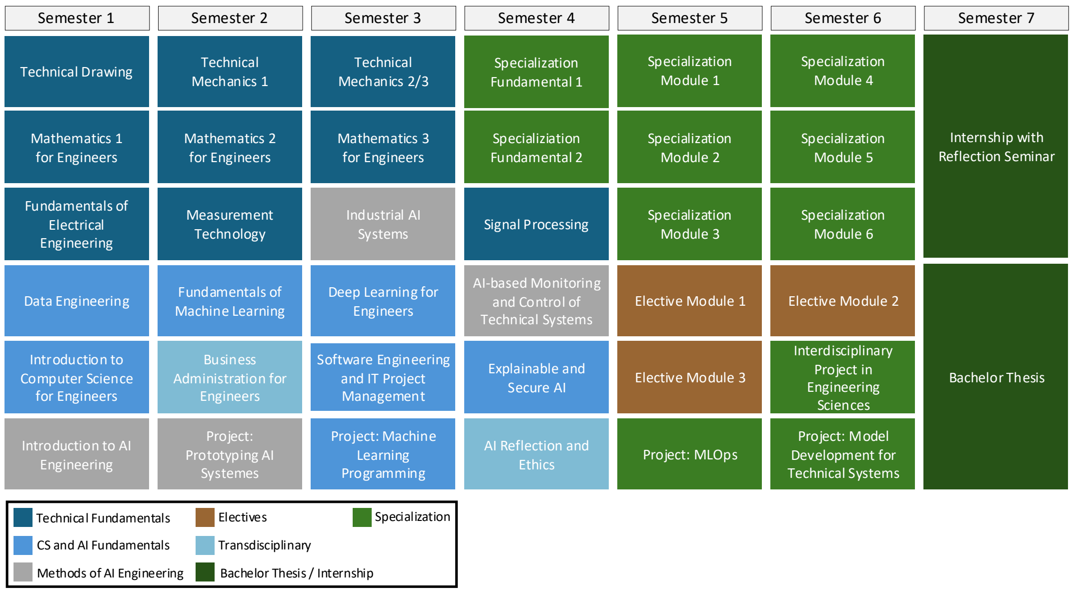

Figure 5.5: Curriculum of the study program AI Engineering over seven semesters. Each module has a load of 5 credits, which corresponds to 150 hours.

Competency Profile The underlying competency profile was developed as part of the curriculum development process, which focused on what competencies students should have upon completion of the program. As described in the previous section, it took into account the latest research and industry perspectives [pub:12] and was developed through collaborative discussions among the stakeholders involved in the curriculum development [pub:23]. The targeted competency profile of the program can be divided into the categories of mathematics, engineering, computer science, AI, engineering specialization, process- and systems-oriented work, and transversal competencies. An overview is given in Table 5.1.

Curriculum According to the backward design, the program-level competency profile was used to develop a curriculum to achieve the targeted competencies. The seven-semester curriculum (210 credits) is divided into two parts. First, students take a core curriculum in semesters 1-4 that aims to provide a foundation in engineering, mathematics, computer science, and AI, as well as focus on integrative courses and projects that bring engineering and AI together (visualized in Figure 5.5).

After completing the core curriculum, students choose one of five specializations that relate to engineering application areas. In the specializations, students focus on using AI technology in the context of a particular application area, emphasizing working with data and engineering processes from the domain and understanding

Table 5.1: Program level competency profile for the study program of AI Engineering.

Area	**Competencies**
Math	Understand, use, and apply mathematical methods, especially methods needed for AI systems (linear algebra, statistical and stochastic tools, analysis tools, optimization algorithms, machine learning problems)
Engineering	Apply physics and engineering principles to design and develop data-driven solutions Use measurement and sensor technology to collect and analyze engineering data Master control engineering, signal processing techniques, and measurement and sensor technology to collect, analyze, and work with data Design and develop engineering systems that integrate AI and data analytics
Computer science	Design and develop software applications using object-oriented programming Implement algorithms and data structures to solve complex problems in AI systems Apply software design patterns and practices to develop maintainable and scalable software Deploy and manage cloud applications and servers
AI	Collect, organize, and preprocess data to prepare it for AI model development Develop and optimize AI models using libraries and optimization algorithms Visualize and evaluate AI model performance using relevant metrics and validation methods Explain and interpret AI model results and their implications Deploy and monitor AI systems in real-world applications Apply agile development, continuous delivery, and Machine Learning Operations (MLOps) practices to develop and deploy AI systems
Engineering specialization	Understand the fundamentals of the application area and its data-driven aspects Apply data-driven solutions to specific engineering domains Understand the fundamentals of the respective application area and its data-driven aspects Map processes, data, and framework conditions in the application area to AI systems Develop and implement AI solutions that integrate with existing engineering systems
Process & system-oriented work with AI systems	Develop and structure complex problems to be solved using AI systems Plan, implement, and monitor the use of AI systems in a project Perform value-risk assessments to ensure effective and responsible AI system deployment Develop and implement AI systems that integrate with existing business processes and systems
Transversal skills	Communicate effectively with stakeholders from diverse backgrounds and disciplines Work collaboratively in interdisciplinary teams to develop and deploy AI systems Plan, implement, and coordinate projects that integrate AI and data analytics Reflect critically on actions and skills, and adapt quickly to new topics and technologies

the underlying foundations of the application area. Five different specializations are currently offered in this curriculum: (1) agricultural economy and technology, (2) biomechanics and smart health technologies, (3) green engineering, (4) manufacturing, production and logistics, and (5) mobile systems and telematics. In each specialization, students have two core foundation courses and six specialization courses. In addition, they can take three electives and complete three (interdisciplinary) projects. The curricula of all specializations are visualized in Appendix B.2.

5.2.5 Evaluating the Development Process

Procedure The effectiveness of the development approach was assessed using both self-evaluation procedures with the facilitators and quantitative ex-post surveys of participants at the end of the workshop series. The ex-post evaluation focused on key areas such as the implementation and methodology of the curriculum workshops, as well as the level of specificity and successful implementation of interdisciplinary curriculum development within the workshops. Respondents were asked to identify, if possible, a medium for the workshops they attended. The survey can be found in Appendix A.3.

For the survey, all 30 people who attended at least one session were contacted and reminded twice. Of these, 14 participated in the survey. The majority of the fourteen participants were academic staff, three of whom were professors. Half of the respondents identified themselves as computer scientists and the other half as engineers. This also roughly corresponds to the actual distribution in the workshops.

Data Analysis Data was analyzed using IBM SPSS Statistics. The closed-ended items of the survey were reported with extreme values.

5.2.6 Evaluating the Development Outcomes

In order to evaluate the developed curriculum in the formative evaluation, two instruments were used: a curriculum outcome mapping and focus group interviews. The former examined the alignment of the intended competencies of the competency profile and the module learning outcomes of the curriculum. The latter evaluated the curriculum from the perspective of a group of experts.

Curriculum Outcome Mapping Curriculum outcome mapping is a tool used to understand curricula, identify competency gaps, and analyze the alignment of a curriculum to achieve intended outcomes as well as course and competency progression [6]. There are several variations across disciplines and in the depth of analysis, particularly in aligning with the different requirements of disciplines, such as those related to accreditation frameworks.

The competencies of the target competency profile were mapped to the modules of the curriculum, based on the module description of learning objectives and content of the module catalog. The module catalog is a document provided to students that describes the modules at a high level. In total, all 22 core curriculum modules and the 13 mandatory modules per specialization were coded as to whether they partially, fully, or did not introduce certain sub-competencies of the competency profile.

Other work has already identified challenges in the curriculum mapping process, namely the difficulty of interpreting skills and competencies depending on the background of the raters, and the difficulty of determining levels of proficiency and taking into account the relationships between competencies [84]. To address these challenges and ensure the reliability of the coding, parts of the mapping were coded by a second person with a different background, and divergent codings were discussed and resolved. It was also decided to include the content descriptions in the mapping for better context, as the learning objectives for some subjects were not clearly stated and did not provide enough context to map the competencies. After coding, the scores were summed per competency subarea to assess the coverage of the competency. In addition, the average of each competency area (e.g., math, engineering fundamentals) was calculated to see the emphasis on competency groups.

Focus Group Interviews To deepen the understanding of curriculum mapping, focus group interviews were conducted with educators who teach in the curriculum and industry experts. Focus group interviews gather a small, diverse group of people, usually experts in a field, to discuss a specific topic or set of questions, allowing researchers to observe group interactions and gather a range of perspectives [149, 225]. The main reason for using focus group discussions is to generate debate and collective insights on a research topic, revealing the underlying meanings, experiences, and beliefs [239, p. 28]. Participants were selected for their relevance to the topic, age, social characteristics, and comfort with discussion, adding depth and richness to the data through group dynamics [259, p. 655].

A total of six interviews were conducted with 19 people across three groups (two interviews per group). The groups differed as (1) educators who were part of the curriculum development, (2) educators who were not part of the development, and (3) industry experts. The distinction between the groups was intended to avoid positive and negative bias and to assess how the perceptions of the groups differed.

The interviews followed a clear structured guide to allow for comparisons between interviews. The interview guide can be found in Appendix A.4. First, participants were introduced to the agenda and objectives of the interview, and a short introductory round was conducted. Second, participants answered a short survey about their experiences and attitudes toward interdisciplinary programs. Third, the interview focused on the question of how well the competency profile is achieved with the developed curriculum. For this purpose, the participants were given some time to familiarize themselves with the competency profile and the curriculum. Then they voted anonymously and discussed their votes and their reasons in the group. Fourth, the interview addressed the content, acceptance, and expectations of the participants. For example, it was asked how well the curriculum represents the professional requirements of their disciplines and what expectations the participants have of an AI engineer. Fifth, the interview touched on the opportunities and challenges of interdisciplinarity in the program. Finally, the participants were given the opportunity to address any other open issues for discussion, and the interview was closed. The interview guide for industry experts was slightly adapted to their context.

The interviews lasted approximately one hour each. All interviews were conducted by two researchers, one as moderator and the other as observer and note taker. The interviews were audio-recorded and transcribed.

The coding scheme was developed inductively and iteratively per question using qualitative content analysis [208] and stepwise thematic analysis [38]. To ensure a reliable coding process, the interviews were then paraphrased. In the coding phase, each of the three participating researchers coded a subsets of the semi-structured interviews to ensure consistency across interviews.

To ensure reliability of coding, a second coder coded one-third of the interviews, and disagreements were discussed and resolved. The resulting coding scheme is presented in Table 5.2. The data was summarized based on the different interview sections and codes, and compared between the different focus groups of industry, participating, and non-participating educators. In addition, key quotations were marked and included in the results.

Table 5.2: Coding scheme per interview part and coding level 1 and 2 with codes occurring more than one time.

Part	**Level 1**	**Level 2**
General evaluation of the study program	Strengths	Interdisciplinary orientation Practical/project-orientation Diversity of content Curriculum Employability
	Weakness	More innovation possible Employability
	Challenges	Lack of fundamentals/content Small cohorts Provide orientation Realization Practical/project-orientation
	Possible solutions	Cooperation in implementation of study program Information about the content of the modules Increased interlinking
	Improvements	Identification of core practices in the field of AI engineering
Interdisciplinarity	Opportunities	Attractiveness Interlinking Practical/project-orientation Versatility Change of perspective Profiling Holistic view Communication/ technical language
	Risks	Overload Interlinking Implementation Effort Lack of depth
	Challenges	Cooperation during implementation Communication Interlinking
Expectations of an AI Engineer	Expectations	Interdisciplinary working and understanding Professional competencies Communication in different technical languages Practical/project experience Understanding of the overall process Problem-solving strategies Mediating role

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Table 5.2 – continued from previous page

Part	Level 1	Level 2
Curriculum and competency profile fit	Remarks	Confirmation
	Challenges	Provide orientation Representing transversal skills Implementation Deepening and application of competencies Interlinking Cooperation during implementation
	Criticism	Missing fundamentals/content
	Positive	Practical/project-orientation
	Risks	Overload

5.3 Evaluation of Development Process

5.3.1 Self-Evaluation of Facilitators

The experience of workshop facilitators suggested that it is important to keep the format of the workshop flexible, to allow enough time for different perspectives to be heard, and to give everyone the space to contribute. Through the feedback gathered from participants, the workshops were adapted to the needs of the participants, for example by shortening the session time or including an input part to get everyone on the same page. In contrast to a thematic focus, it was important to go through the content objectives several times in order to absorb interdisciplinarity. This means that certain aspects, such as the competencies or the structure of the curriculum, were addressed in several sessions in order to allow for discourse and agreement among educators from different disciplines. A key issue that arose in this context was the question of what foundations are necessary and whether students should first have established basic courses before moving on to applications and projects.

In addition, intensive preparation and follow-up as well as the formulation of clear tasks were essential to involve all participants in the process. This was especially important as participants changed from one curriculum workshop to another. The online format proved to be useful and made it possible to bring the different stakeholders together in a digital space despite the physical distance. In addition, digital tools such as online whiteboards made it easy to document the process and outcomes, and digital meeting tools allowed for quick shifts from group to plenary discussions. Overall, the facilitators perceived the development process as successful, but also as a learning experience in terms of adapting to the real needs of the educators in the process.

5.3.2 Ex-post Evaluation of Participants

These experiences can also be confirmed by the ex-post evaluation. The curriculum workshop was evaluated in terms of implementation, method and interdisciplinarity.

Implementation of the Curriculum Workshops The implementation of the curriculum workshop sessions was assessed through eight individual items using a 5-point Likert scale from *1 - do not agree at all* to *5 - agree completely*. Overall, the implementation was rated very positively by the majority of the 14 respondents (ten or more of the respondents agreed with good preparation, use of tools was helpful, appropriate duration). Eleven of the 14 respondents found working in small groups helpful for the idea generation process (scores 4 + 5 on the scale). The preparation was perceived as good by 13 of the 14 respondents, but the follow-up was perceived as good by only ten.

Method of the Curriculum Workshops Respondents were also asked to rate eight individual items regarding the methods of the curriculum workshop. The majority of respondents (12 out of 13) agreed that the curriculum workshop sessions were helpful in exchanging ideas and perceptions and that it was a participatory method (scores of 4 and 5 on a scale of *1- do not agree at all* to *5 - agree completely*). An important goal of the curriculum workshop method as part of course development was the creation of the competency profile and the development of the module matrix. Eleven out of 13 found the methods helpful in creating the competency profile, and nine out of 13 found them helpful in developing the module matrix. However, only six of the 13 respondents agreed with the statement "The curriculum workshop method was helpful in working out formulations." (4 and 5 on the scale).

Interdisciplinary Cooperation and Participation Almost three-quarters of the respondents (9 out of 13) agreed with the statement that the curriculum workshop is a suitable tool for taking interdisciplinary perspectives into account. The majority of respondents agreed with the statements "I was able to work productively with representatives of other subjects and/or subject cultures" (11 out of 13), "I consider the interdisciplinary cooperation to be profitable overall" (12 out of 13), and "Difficulties in understanding between subjects and/or subject cultures were addressed by the moderation" (11 out of 13)[3]. Some participants reported problems with interdisciplinary cooperation in the workshops, but the frequency of these problems was estimated by most to be only occasional.

[3] In each case values 4 and 5 on a scale from *1- do not agree at all* to *5- agree completely*.

Open Responses In addition, survey participants were asked in an open-response format to identify the strengths and weaknesses of the curriculum workshop as a method for interdisciplinary curriculum development. Participants emphasized the need to clearly articulate goals at the beginning to ensure appropriate expectations. In addition, an appropriate group size and representation of all stakeholders was considered important. As a strength of the format, participants highlighted that it is very well suited to actively involve all stakeholders in the development process. Participants also mentioned that the method ensures that the results are practical and application-oriented. In addition, it was mentioned that the complexity of the development can be addressed through the intensive exchange during the workshops. Last, the structured approach of the curriculum workshop method was also positively highlighted.

General Recommendation Overall, eleven of the 13 respondents found the use of the curriculum workshop method to be recommendable when creating a new interdisciplinary program (8 of 13 "Yes, definitely"; 3 of 13 "Yes, probably"). Only two of the 13 respondents felt that the method was not recommendable.

5.4 Evaluation of Development Outcomes

In the following, the results of the formative evaluation are reported, including the curriculum mapping and the qualitative analysis through a focus group interview with experts.

5.4.1 Curriculum Outcome Mapping

Curriculum outcome mapping was used as a checkpoint to ensure a consistent and practical design and to assess whether the modules could achieve the desired competency profile.

Descriptive Elements The total credit load for the program is 210 Credit Points (CP). In addition to the internship and the Bachelor thesis, a total of five explicit project modules (25 CP) have been identified. Three modules (15 CP) are electives and were not included in the curriculum mapping. The curriculum consists of a core curriculum (110 CP) and a chosen specialization (100 CP).

Program Level Coverage of Competencies In the mapping, the subdimensions of all competency areas were coded on three levels (*0 - not covered, 0.5 - partially covered*, and *1 - covered*). To understand the coverage and focus, the summed scores per competency area and the average of the summed subdimensions for the core curriculum and specializations are reported in Table 5.3. In addition, the detailed mapping, including all courses and competency dimensions, can be found in Appendix B.3.

Table 5.3: Coverage of competency areas after core curriculum and after each specialization. Per area (Math (M), Engineering (Eng), Computer Science (CS), Artificial Intelligence (AI), Engineering Specialization (ES), Process- and Systems Thinking and Working with AI (PS), Transversal (T)), the sum $\sum$ and the average of the mapped sub-competencies $\overline{c}$ are reported to understand the emphasis and coverage of the competencies. The complete mapping can be found in the appendix Appendix B.3.

	M		**Eng**		**CS**		**AI**		**ES**		**PS**		**T**	
	$\sum$	$\overline{c}$	$\sum$	$\overline{c}$	$\sum$	$\overline{c}$	$\sum$	$\overline{c}$	$\sum$	$\overline{c}$	$\sum$	$\overline{c}$	$\sum$	$\overline{c}$
Core Curriculum	5.5	0.9	9.5	1.4	3.0	0.8	18.5	2.6	1.0	0.5	6.5	2.2	5.0	1.3
S1: Agricultural economy and technology	5.5	0.9	10.5	1.5	4.0	1.0	27.5	3.9	8.0	4.0	11.0	3.7	13.0	3.3
S2: Biomechanics and smart health technologies	5.5	0.9	10.5	1.5	4.0	1.0	29.5	4.2	6.5	3.3	12.0	4.0	13.5	3.4
S3: Production, manufacturing and logistics	7.0	1.2	11.5	1.6	4.0	1.0	29.5	4.2	7.0	3.5	11.5	3.8	12.0	3.0
S4: Green engineering	6.0	1.0	10.5	1.5	4.0	1.0	28.0	4.0	7.0	3.5	10.5	3.5	13.5	3.4
S5: Mobile systems and telematics	5.5	0.9	11.0	1.6	4.0	1.0	28.5	4.1	8.5	4.3	11.5	3.8	12.0	3.0

Coverage of Competencies The results indicate that the curriculum is aligned with the targeted competency profile, but the coverage varies across the different areas. As indicated by the average values $\overline{c}$ in Table 5.3, there is a strong emphasis on AI-related competencies, engineering specializations, process/systems-oriented work with AI, and transversal skills. However, there are also sub-competencies, particularly in mathematics and fundamental machine learning topics, that are only partially covered, indicating that these topics are present but may not be thoroughly addressed in the curriculum learning outcomes or module descriptions. In addition, there is limited explicit emphasis on the fundamentals of computer science and data science, and deeper reinforcement of these skills can only be explicitly identified in the project modules.

The curriculum focuses more on AI system development and prototyping, with less coverage of the skills needed to deploy, monitor, and maintain AI systems in production. For example, server and cloud application skills are only covered in the MLOps project module, and ethical considerations are only explicitly covered in the core curriculum.

Overall, the mapping shows that the curriculum follows a logical progression with no clearly identified gaps, with earlier modules focusing on basic skills and their integration, and later modules building on these to develop more advanced, specialized skills. Integration and transfer occur mainly in the project modules and in specialized interdisciplinary modules.

5.4.2 Qualitative Analysis through Focus Groups

Participants A total of 19 experts participated in the six focus group interviews. Of these, five were industry experts and 14 were educators. The educators were divided into two groups: eight participating educators who were involved in curriculum development and six non-participating educators. All educators had at least four years of teaching experience, with the participating educators having slightly more experience on average. Almost three-quarters of the educators had previous experience in curriculum development, while half of the non-participating educators had no such experience (n=3). The industry experts had several years of professional experience, with most having at least seven years, and almost all working with AI on a daily basis. Overall, almost all respondents had a very positive or positive attitude towards interdisciplinary programs in general, with only two educators expressing a neutral attitude.

Effectiveness and Consistency: Curriculum and Competency Profile Fit When asked about the effectiveness and consistency of the curriculum's fit with the competency profile, participants rated the fit overall as good, with detailed ratings provided in Table 5.4.

Table 5.4: Reported fit of curriculum and competencies per status group. Participants had to rate their initial response before discussing the question "How well is the competency profile achieved with this curricular composition of the modules?". Ratings on a five-point Likert scale ranging from *1-not good at all* to *5-very good*. Number of participants per group N, mean of rating, and standard deviation (SD).

Group	**N**	**Mean**	**SD**
Participating educators	8	4.50	0.53
Non-participating educators	6	3.17	0.75
Industry	5	3.80	0.45
Total	19	3.89	0.89

In terms of the reasons for their perceptions, participants criticized missing content (n=12) such as deployment and operations, preprocessing, and generative AI, as well as perceived gaps in the foundations of computer science. There were also concerns about the true depth and application of the competencies, for example in the context of programming (n=9), and the challenge of integrating and linking domains (n=8). Some felt that the implementation of certain competencies could be difficult given the curriculum load (n=6). Representing and teaching transferable skills in the curriculum was also seen as a challenge (n=6). Participants also identified the implementation of the program in general (n=4) and providing students orientation (n=4) as challenging. For example, participants stated:

"[...] how well the bridge between engineering and AI can be built afterwards really depends on how this can really be implemented. [...] We have a bit of a challenge to keep the thread going from the fundamentals back here into the specialization." [PE5]

"We will still see a lot during the implementation where there may be gaps and where the theoretical plans may not work. But from what we have been able to prepare now, it fits very well." [PE7]

Throughout the interviews, overburdening of students was identified as a risk factor (n=8), mostly related to overburdening by interdisciplinarity and diversity of competencies for a Bachelor's program. On a positive note, participants highlighted the practical and project-oriented nature of the curriculum (n=4).

Practicality: Strength and Weaknesses To further understand the practicality of the program, participants were also asked what they perceived to be the strengths and weaknesses of the program. Strengths mentioned were the practical and project orientation (n=5), the interdisciplinary orientation of the program (n=3), the curriculum in general (n=2), its diversity (n=2), and the potential employability (n=2). Weaknesses mentioned were that the development could have been more innovative (n=3), that graduates might not be industry-ready after a Bachelor's degree (n=2), and single mentions of the high diversity as a risk of losing orientation, lack of foundation, and lack of time and opportunity to deepen skills.

Fit to Disciplinary Expectations To understand the diversity of disciplinary expectations, participants were asked to give a subjective rating of the curriculum's fit with their disciplinary expectations. Because this subjective rating is not comparable due to different interpretations of expectations and the question, overall observations are reported. Participants generally felt that certain parts of the curriculum lacked the depth expected in more traditional programs such as computer science or engineering. A common concern was that there was a lack of foundational coverage in some areas, with too much breadth and not enough depth across the curriculum. Specifically from a computer science perspective, participants felt that the modules may not provide enough programming depth and fundamentals for students. While the interdisciplinary nature of the program was seen as a strength, it was also seen as a potential challenge in meeting disciplinary expectations and providing sufficient depth in the various areas covered.

Opportunities and Risks of Interdisciplinarity in the Program Participants discussed the opportunities and risks of the interdisciplinary nature of the program. Opportunities mentioned included integration and linking of content (n=6), practice and project orientation (n=5), diversity of content (n=4), profiling (n=4), development of a holistic view (n=4), communication across disciplines (n=3), change of perspective (n=3), and improved employability (n=2). As one industry participant noted, *"the greatest opportunity of interdisciplinarity is that [...] graduates actually also have opportunities in their professional lives outside of these five specializations [...] because they have a background that is relatively universal." [I3]*

Risks included challenges in integrating content (n=11), potential overload because of interdisciplinarity (n=5), effort and cost of implementation (n=3), lack of depth (n=2), and overall difficulty of implementation (n=3). One participant explained: *"I see the risk that it really is an overloading demand. [...] Everyone has to think for themselves, how can I somehow link what I learn from measurement technology with the basics of machine learning, and I think that's actually a difficult transfer." [I2]*

Challenges included cooperation across domains in implementing the program (n=4), communication with the students in the program (n=2), marketing to the target group, and setting expectations for the program (n=2).

Participants viewed the integration of courses and domains as an opportunity (n=6), a risk (n=11), and a challenge (n=8). While integration was seen as beneficial, concerns remained about effective implementation and potential fragmentation of knowledge.

As one participant noted, *"If it's all integrated really well and works, then I think it's a pretty cool program [...] The risk is that if there's an issue at any point, it can quickly turn out really bad for the students." [NPE3]*

Potential Challenges and Improvements Other challenges mentioned by the participants were the implementation of the program (n=6), especially regarding the integration and organization of interdisciplinary content and the question if educators can adapt to students. In addition, small student cohorts were seen as a challenge, especially in the context of implementing and filling the five specializations (n=4). Giving orientation for students (n=4) and the practical orientation (n=3) were also identified as challenges.

In terms of program improvements, participants had several suggestions. Two participants recommended identifying core practices and competencies and emphasizing them in the curriculum. One participant each suggested increasing communication about the interplay of modules and courses, reviewing the sequencing of modules, changing the orientation of technical topics, moving ethical discussions to a later semester, and preparing students' communication skills.

As potential solutions, participants suggested supporting interlinking and integration (n=3) and collaborating on implementation (n=3). This could be achieved through a meeting of educators who teach in the same semester or through improved documentation of the content accessible to all educators, i.e., providing information about the modules or the technologies and tools used (n=3) and providing information to students through additional events (n=1).

Differences from Participation in the Curriculum Development Overall, the interviews showed that people who participated in the development of the program were able to contextualize the outcome of the development to a greater extent, and also to justify and defend the design choices made in the development, as observed in this interview excerpt:

"[...] This is an interdisciplinary degree course. This means that there is always the necessity or the fact that we can't train a jack-of-all-trades in a degree program like this and that we have to cut back in certain areas. [...] We have also discussed what can be achieved in many workshops and it now fits in with what we wanted on paper." [PE7]

Positive highlights such as the practical orientation (participating educators (pe)=5), the interdisciplinary orientation (pe=3) and an optimized curriculum (pe=2) were only mentioned by participating educators. However, participating educators also acknowledged the challenge of providing orientation for students (pe=4), marketing (pe=2), and the reality that students are only Bachelor graduates (pe=2). Participating educators also had more concrete solutions such as collaboration in the implementation of the program (pe=3), stronger integration of content and modules across semesters (pe=3), and providing information about the content of each module across educators (pe=3).

"[...] What you can basically say at this point is that we have enough room in the curriculum for these skills to develop, and we give people the opportunity and have many projects where they can also be honed in practice. [...] But on the other hand, it has to be said that we have taken a very ambitious approach here. Due to the interdisciplinary nature of the program, we now have various disciplines that need to be represented here. We have pretty high expectations of what people should be able to do afterward, and I think that's a good thing. The fact that we don't yet have any experience of how people will actually cope with the curriculum means that I think it's good for now and not very good." [PE4]

Non-participating educators emphasized the opportunity to develop a holistic view (npe=3) and highlighted the challenge of small cohorts in the context of developing content for the specialization (npe=3 vs. pe=1). Non-participating educators also stated multiple risks such as integration (npe=6 vs. pe=1), overload for the students (npe=3), the implementation of the study program, especially with respect to the integration of multiple modules in reality (npe=2), and missing depth in the content (npe=2).

Overall, educators also agreed in their assessment of multiple aspects. An example was the assessment of interdisciplinarity, where the linking and integration of several disciplines was seen as an opportunity (npe=2 vs. np=3), employability (npe=1, pe=1). Similarly, diversity (npe=1 vs. pe=2), and the risk of too much effort for educators was mentioned by both groups (npe=1, pe=1). Additionally, educators from both groups emphasized communication in different professional languages (npe=1, pe=1) and interdisciplinary skills (npe=2 vs pe=3) as an expectation.

Differences between Industry and University Perspective Overall, the program was perceived positively by participants from industry, indicating a good fit in terms of employability and practical aspects, as well as highlighting the relevance of the program.

"[...] With this degree program, you really almost exactly reflect what we also expect from our employees. We would probably say that the training isn't over yet, but that someone will probably have to specialize in something [...]. But the topics that are covered are great. And when I look at things like manufacturing, production, and logistics, for example, if the people also have an idea of simulation methods, a bit of what happens in a factory or machine tools, that's really practical in any case and really an everyday toolbox for my work." [I2]

To understand the differences between educators and industry, participants were asked what expectations each group had for an AI engineering graduate. Numbers are given in absolute terms, but note that the groups are unequal (14 educators, 5 industry participants). Both groups expected professional competencies in AI concepts and technologies as well as data (educators (e)=7, industry (i)=5) and strong problem solving skills (e=8, i=4). In addition, both groups emphasized expectations for communication across disciplines (e=2, i=1) and a holistic view of data and AI processes (e=2, i=2).

"My expectation of the AI engineer is that they are the first point of contact for potential AI projects to see whether they can be implemented and they also go through a company and see potential themselves where AI could make progress. [An AI engineer] can plan, coordinate, and support AI projects. He is also able to do a bit of prototyping. What I don't explicitly expect from an AI engineer is that they are already developing a commercial solution. I see that more as a computer scientist. So for me, it's really about prototyping, dealing with methods, proof of concepts, and then actually supporting the AI project in collaboration with specialists from the respective disciplines." [PE5]

"I think due to the strong practical orientation [...] I would also expect them to have really internalized this process idea, for example, this AI engineering process from problem understanding to implementation and tracking. That's something I wouldn't expect from normal computer science students." [PE4]

Educators emphasized interdisciplinary understanding, collaboration, and acting at the intersection between domains (e=5), while industry participants expected graduates to have gained practical and project experience (i=2) and to be able to act as a mediator between domains (i=2).

"[...] bring sufficient expertise from their application domain, understand the data that is generated, and then know how to develop customized AI solutions." [NPE6]

"To put it simply, my expectation is that they will ask the right, burning questions. On the basis of the data, on the basis of the information he collects, simply being able to look behind the data, so to speak. I wouldn't necessarily expect them to have the full domain knowledge [...] but he can handle the data and [...] filter and derive the models that can then be used in a stringent, comprehensible, and argumentatively plausible manner." [I3]

At the same time, it was mentioned that the students were only undergraduates (n=2) and that more in-depth and advanced studies might be needed.

"So perhaps the first expectation would be that I don't expect too much. I mean, they've done a Bachelor's degree and know the vocabulary, they've done a few projects and you can definitely put them into projects with a certain amount of responsibility." [I1]

Overall, industry participants were more focused on practicality, as indicated in this interview snippet: *"[...] the challenge is to give the students the tools or the skills to get the data they need, in the quality they need it. Because, of course, my experience with students is often that the tasks they are given during their studies work. The data you get there, you know that in the end, it will somehow be possible to program an AI with it. But the reality is often different. And having experienced this challenge yourself as a task - how do I get the data I need to program my AI in the end - is something that could perhaps be quite helpful." [I4]*

Similar to educators, industry participants also criticized the lack of content (i=6, educators=7), but the industry focus was more on practical implementations and deployments.

"[...] AI only works by putting it into practice. Purely theoretical AI is pointless. And that's why one of the points of criticism or questions for me is how much of the computer science part is also practical here. [...] how do you really build a meaningful architecture, a maintainable architecture, the compromise between perfect theory and reality, what can you really implement, where are the limits, where not." [I4]

5.5 Discussion

This chapter contributes to the understanding of aspects of interdisciplinary curriculum development. In particular, it examined a case study of curriculum development at the intersection of AI and engineering. In addition to examining the process and validating that the developed curriculum builds the targeted program-level competencies, the main findings concerned educators' perceptions of the development process and outcomes. Below, the key findings are contextualized within the broader field of research.

5.5.1 Main Findings

Participatory method of curriculum workshops supports interdisciplinary curriculum development. Overall, the results of the process evaluation in this case study indicate that the curriculum workshop method can be considered a suitable format for interdisciplinary curriculum development, especially for novel program development. It allowed for a creative exchange format, the collection and specification of ideas with the participation of the disciplines involved, and does not require guidelines from existing programs.

The format is well suited for sharing ideas, collecting and bundling ideas, creating team spirit, and facilitating collaboration among participants across faculty and university boundaries. The given structure with room for flexibility particularly supports interdisciplinary curriculum development [pub:23]. The results in the context of this case study emphasized that taking individual interests into account and planning sufficient time for them are a key aspects of interdisciplinary collaboration in the workshop sessions. In addition, it was important to tackle certain tasks and questions several times to allow participants to take different perspectives. Participants felt that their interests were sufficiently taken into account and that they were able to participate productively throughout the workshop series.

The experiences of the case study demonstrated that the curriculum workshop method is suitable for creative brainstorming and consensus building, but not so much for the concrete formulation of outcomes, e.g., in descriptions of a competency profile or module. In this experience, connecting the findings, creating condensed outcome reports and discussing them in the next session was a way to move forward and not get stuck in details. When working with different cultures, backgrounds, and experiences, it was important to create a mutual understanding of the issues, e.g., by providing input or context.

Curriculum development for new programs requires more exchange and development than curriculum development based on existing competency profiles [5]. The results of this caste study emphasized that the curriculum workshop approach can provide an appropriate structure for such new development. Therefore, the approach can give new impulses to educators, curriculum developers and faculties on how to approach interdisciplinarity in curriculum development, especially with a focus on the integration of AI in engineering education. This also addresses the question of what knowledge and skills are relevant for future engineers to be prepared for their future jobs [106, 217]. In addition, findings and considerations from this work can be applied to interdisciplinary curriculum development for other future trends, such as the intersection of sustainability and engineering [17, 158, 312].

The AI curriculum developed for engineering is expected to be effective. The results indicated that the evaluated curriculum in the case study provides coverage of the targeted competencies. The modules were placed in a coherent structure that progressively builds foundational skills in initial modules before moving on to more complex topics. Thus, the curriculum mapping results underscored the expected effectiveness of the curriculum in achieving its intended outcomes and consistency. Although educators and industry participants identified different areas for improvement, the focus group interviews supported these findings, with educators and industry participants generally rating the curriculum positively in terms of its fit with the competency profile. In particular, participants appreciated the practical and project-oriented nature of the program, as well as its interdisciplinary nature, which is consistent with the goal of making students employable and able to work across domains. However, the interviews also identified potential missing content (e.g., deployment, operations, pre-processing, generative AI, and foundations of computer science). In addition, potential challenges in deepening and applying competencies such as programming skills and interdisciplinary integration were identified, indicating some potential mismatches between what is taught and how well students are able to apply these skills.

Participation of multiple stakeholders supports ownership of the program. Previous studies showed that personal factors significantly influence curricular choices and thus perceptions of quality of educators [172, 292]. Thus, it could be expected that participation in curriculum development would lead to different views of outcomes. When comparing participating and non-participating educators, participation in curriculum development was found to foster a greater sense of ownership and understanding in the participating group, which positively influenced their perceptions of the program. This implies that participatory approaches to curriculum development should be included in the design, especially for interdisciplinary programs. It also highlights the diversity of perspectives that underscores the value of involving diverse stakeholders in the development process.

Educators perceive interdisciplinarity as a strength, but find it challenging to implement at the curricular level. In the context of interdisciplinarity, the interdisciplinary nature of the program was seen as a significant strength, with opportunities for students to gain holistic views, communicate across disciplines, and transfer skills between domains. The integration of content across disciplines was also highlighted as an advantage. However, interdisciplinarity also poses challenges, including student overload because of the breadth of competencies required and the difficulty of effectively integrating content across disciplines and across the curriculum. This raises concerns about students' ability to cope with the demands and to make connections between the different areas of study. Although interviewees felt that the curriculum was well aligned with the intended interdisciplinary competency profile, they highlighted the difficulty of effectively teaching certain competencies and achieving the necessary depth given the curriculum load. This suggests that while the curriculum is designed with the right elements, its effectiveness may be limited by time and resource constraints, especially in the context of integrating multiple domains.

5.5.2 Implications for Research and Practice

From the results of the chapter, five main implications for interdisciplinary curriculum development in practice and further research can be identified.

Flexibility and transparency are key to the development of interdisciplinary curricula. One part of the chapter focused on the relevance of the curriculum workshop method for designing the curriculum of a new course characterized by complex content and the connection of different participants. The workshops conducted were based on a model developed from the literature. The main goal was to develop the necessary (content) foundations of the course and to implement them in a coherent curriculum. Overall, the results of the implementation included the curriculum profile, a competency profile, learning outcomes, and a module matrix.

The main findings of the implementation of curriculum development using the curriculum workshop method can be summarized as follows: In order to involve all participants in the process, it helps to create transparency in the implementation, to prepare and follow up the processes well, to design them openly, and to formulate expectations and tasks clearly [pub:23]. The format should be flexible in terms of the design of the phases and the specific implementation of the individual workshops and should be based on the needs of the participants [pub:1, pub:23]. It can be conducted in an online format which supports the collaborative development and documentation of content despite the physical distance [pub:23].

Developing interdisciplinarity in curriculum requires more design considerations and scaffolding of content integration. While there is a call for more interdisciplinary curricula and courses in engineering education [312], the design of these is more complex than discipline-specific courses. The study finds that the integration of knowledge from different disciplines, particularly in facilitating transfer between them, is particularly challenging. This connects to previous findings of Mac Leod and Van der Veen [197], who highlighted that scaffolding interdisciplinarity is particularly difficult in Bachelor courses, which are often taught to a broader audience of students from multiple study programs. Thus, integration across disciplines requires more precise scaffolding for students, consistent with the learning theory of constructivism [293], which emphasizes the importance of learners actively constructing knowledge by connecting new information to their existing understanding.

The importance of integration emerged as a consistent theme in all of the expert interviews. This connects well to previous studies on curriculum design where the aspect of integration is discussed broadly under the theme of integrated curriculum design [9]. When institutions lack the resources to completely redesign and explicitly teach all modules for a program, they must find a balance between existing modules and modules that focus on transfer and integration across disciplines. However, more empirical work is needed to understand the conditions and interventions that support the implementation of scaffolding integration across the curriculum.

Interdisciplinary programs require more communication with students. Scaffolding interdisciplinary programs for students also involves a strong communication aspect. Ideally, students understand how each module relates to their target competency profile and how they are interrelated. In practice, program documents are rarely fully picked up and read by students and often do not provide a clear understanding of the program.

This can be addressed by a number of measures all of which require more empirical research to understand their effectiveness in addressing the problem. One direction is the formulation of a set of core practices that visualize and communicate the core competencies of a program. Another direction is a targeted use of modules or projects that integrate or communicate how competencies are combined in the curriculum [230]. Here, educators have a strong responsibility to choose appropriate problem designs to scaffold interdisciplinarity [197]. Finally, pre-arrival courses [301] in the transition to higher education could be used to communicate the interdisciplinary aspects of the program.

Educators need horizontal and vertical communication across the curriculum. Another finding of the interviews was the importance of vertical and horizontal lines of communication across the curriculum, especially for interdisciplinary programs. This means communication between educators teaching modules in the same semester (vertical) and educators building on each other's module teaching in subsequent semesters (horizontal). This connects again to the aspect of integrative curriculum design [9].

In the context of this case study, educators expressed that, especially in these interdisciplinary settings, it is more relevant for them to understand what has been taught and what formulations have been introduced. Further studies should include a better understanding of these vertical and horizontal lines of communication and how they affect the quality of student outcomes.

Reference curriculum for AI in engineering. In addition to advancing the understanding of interdisciplinary curriculum development, the chapter also provides educators and curriculum developers with a practical reference curriculum for an AI in engineering program. This can be adopted in different contexts and provides a first step towards curriculum scholarship on AI curricula in different domains [57, 163].

5.5.3 Limitations

The findings and implications must be contextualized with certain limitations. First, the presented evaluation and findings are based on the implementation of one curriculum workshop series. Therefore, implementation in a different setting would provide more insight into the generalizability of the findings. Second, the participants in the workshops were not fixed throughout the development. Thus, participants were asked to evaluate the entire approach as a series of workshops rather than individual sessions. Third, the chapter focused on evaluating the development of the curriculum rather than its implementation. Thus, this work provides a snapshot in time that focuses on the conceptual development of the intended curriculum and has not yet collected valid data on student success at the end of the program or other variables that depend on educator effectiveness (curriculum implemented and achieved). Moreover, it must be considered that a program of study takes place in a socio-cultural context that also influences a student's learning experience [152, 174]. At the same time, the work still provides significant value because the identified strengths and weaknesses and the problems identified will be communicated to educators in the program, potentially leading to improvements through adaptations in course structures and communication. In addition, the in-depth analysis of a case study also identified design considerations for the development of interdisciplinary degree programs and curricular scholarship [163]. Fourth, the curriculum mapping was conducted based on the module descriptions provided by the author without further information, validation, or context from the educators of the modules. This design choice ensures reproducible results, but does not take into account implicit information from the educators of the modules. Finally, the focus group interviews were conducted with a subset of educators, all of whom provided their observations based on their experiences, which may be influenced by personal factors of the educators, such as their beliefs about education or their view of their own discipline [292]. To reduce bias in the focus groups, emphasis was placed on having a diverse group of educators and industry participants to provide a diverse range of opinions. In addition, all interviews were conducted in German and quotes were translated, which could lead to loss of meaning in translation.

5.5.4 Future Research Directions

There are three main directions for future work. First, to conduct further evaluation measures to include more student perspectives in the development process and to assess the actual practicality and effectiveness of the curriculum. Second, the developed curriculum should be further compared with similar developments in order to propose design principles for the development of AI in engineering programs in different contexts. This analysis can also inform further changes in engineering accreditation standards. Third, the implications of the results of this study need to be further analyzed. For example, more empirical evidence on interventions such as horizontal and vertical communication among the educators or student communication for scaffolding interdisciplinarity is needed.

5.6 Summary

Situated in the context of research on curriculum development at the program level, this chapter targeted the curriculum development of an interdisciplinary curriculum at the intersection of AI and engineering. Addressing the broad question of *how to develop and evaluate an interdisciplinary AI curriculum*, it examined the case study of AI Engineering, a novel program development, and explored the process and development outcome perspectives. The chapter applied the participatory approach of curriculum workshops to the case study and found that the method is a suitable format for interdisciplinary curriculum development. The strength of the development approach laid in a collaborative and structured working environment that allows for the consideration of multiple disciplinary perspectives. In addition, the development approach can be adapted to the needs of each group. At the same time, the evaluation showed that the method is suitable for generating new insights, but not so much for the concrete formulation of outcomes.

The evaluation of the development results demonstrated that the developed interdisciplinary curriculum is expected to be effective and practical, as validated by educators and industry. In addition to validation, the evaluation also provided a practical understanding of the curriculum development outcomes, particularly highlighting the impact of educator participation in the development.

Overall, the curriculum profile and development approach can serve as a reference for similar initiatives at other institutions aiming to integrate AI education into engineering curricula at a macro level. It also contributes to more scholarship on curriculum development in higher education [163], especially in interdisciplinary contexts and dynamic environments of AI. The next chapter will focus on the micro level of individual educators, aiming at the identification and integration of domain-specific AI competencies in courses.

6 Supporting Educators in Integrating AI Competencies in Courses

After establishing a conceptualization of domain-specific AI competencies in engineering education in Chapter 4 and an operationalization at the program level in Chapter 5, this chapter focuses on educators. In particular, it addresses the question of how to support educators in integrating AI competencies into their courses.

Following an educational design-based research approach [212, 257], this chapter introduces and evaluates the *AI Course Design Planning Framework* as a visual and participatory development tool. The framework aims to provide a rapid design tool that guides through the development of domain-specific AI courses. Through its simplicity, it can support rapid iterative and participatory course development.

This chapter is based on peer-reviewed articles [pub:19, pub:24].

6.1 Research Context

Contextualizing Course Development Following the established system view (Figure 6.1), this chapter focuses on the micro level of the educator and in particular on supporting educators in integrating AI competencies into courses. As illustrated in Figure 6.1, courses are influenced by several factors. First, they reflect competency definitions and technology developments. In addition, societal and industry needs may influence the targeted learning outcomes or activities. At the same time, courses must meet institutional quality standards. The greatest influence, however, is the educator who shapes courses with his or her knowledge, beliefs, experiences, and identity.

Need for Guidance in Course Development in AI Education As noted in Section 3.1 and Section 3.4, educators play an important role in transforming curricula and courses in higher education. At the same time, they face the challenge of adapting

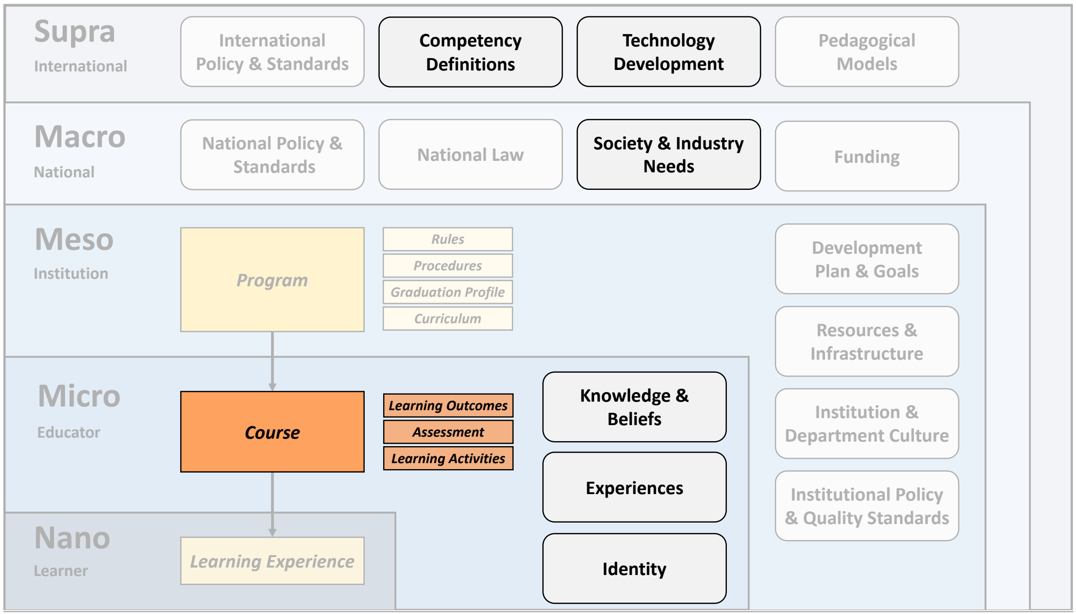

Figure 6.1: Course development in the system model of influences on programs, courses, and learning experiences at different levels. The visible light gray boxes indicate relevant influencing factors that influence or are influenced by course development.

content and methods to new developments in AI. As discussed in Section 3.3.4, educators need to respond to new AI developments in terms of reflecting on learning outcomes, but also adapting learning activities and assessment methods. From the student perspective, recent studies show that students outside of computer science do not feel adequately prepared for the increasing integration of AI in their fields [256, 285] and are increasingly calling for changes in curricula and courses [127].

Thus, educators are faced with pressures and demands from multiple perspectives. To date, however, there are insufficient support structures and tools to help educators adapt to these realities, especially in changing curriculum content. Focusing on the educators themselves, previous research has highlighted several challenges, such as educators' competencies in AI [193, 235] and an unclear systematic approach to developing AI courses [233]. In addition, Eaton and Epstein [78] reflected on the development of the AI part of the ACM CS curriculum 2023 (see Section 3.3) that even AI experts have difficulty selecting relevant competencies. Thus, the question remains, especially for educators teaching in their respective domains, how best to integrate relevant AI competencies into their courses.

Research Questions and Contribution Central to this chapter is the overarching question of *how educators can be supported in integrating domain-specific AI competencies into their courses*. In particular, it focuses on the following sub-questions around the design prototype:

- *RQ 3.1: How can a structured framework effectively support educators in developing domain-specific AI courses?*
- *RQ 3.2: How do educators perceive the usability and usability of the course design framework in the context of developing domain-specific AI courses?*

Overall, the following chapter contributes to a theoretical understanding of systematic course development of domain-specific AI course content for educators.

Chapter Outline The rest of the chapter is organized as follows. Section 6.2 describes the design-based research methodology along the design iterations, including the data collection and evaluation tools. Section 6.3 provides an overview of the artifact. Section 6.4 presents the quantitative and qualitative evaluation results from both evaluation cycles. Section 6.5 concludes with a discussion of the main findings, implications, limitations and future research directions.

6.2 Method and Materials

6.2.1 Design-Based Research Approach

This section introduces the first three iterations of a design-based research project [10, 43]. The goal of the project was to structure and facilitate the development of AI courses for non-CS students (i.e., students majoring in a field outside of computer science) and to identify potential bottlenecks for implementation. The central design artifact of the project is the *AI Course Design Planning Framework* (see Section 6.3), which has been continuously improved according to the design-based research approach. The characteristics of design-based research reported by Wang and Hannafin [321] have been taken into account, with particular emphasis on pragmatism, theoretical support (i.e., grounded in relevant research), and iteration. In contrast to experimental approaches, hypotheses in design-based research are provided as design solutions rather than specific interventions [18]. In addition, design-based research emphasizes the use of mixed methods to evaluate the design artifact. An overview of the methodological approach is given in Figure 6.2.

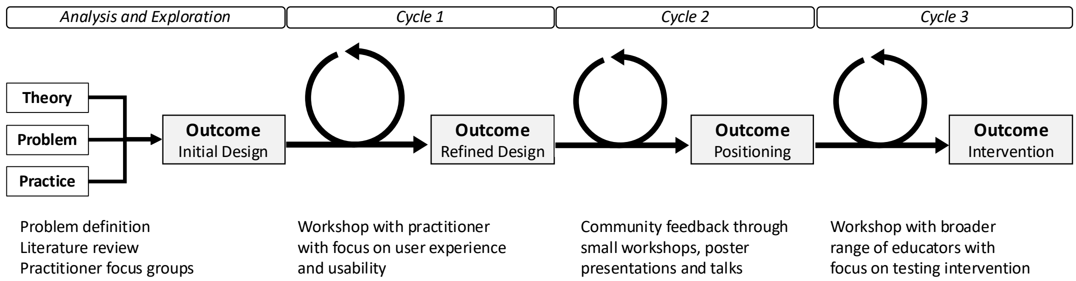

Figure 6.2: Design-based research cycles for the development of the AI Course Design Planning Framework, which include an initial analysis and exploration phase and then three cycles of testing design prototypes with different objectives.

The development cycles were divided into four phases. First, a prototype was developed based on the guiding question of how to identify relevant AI competencies and integrate them into domain courses. The proposed prototype was designed taking into account theoretical approaches from instructional design (see Section 2.3) as well as feedback and challenges from practitioners as experienced in workshops.

According to design-based research procedures, usability testing of a given (pedagogical) tool is often conducted as a first step in the process [118]. Thus, the first evaluation cycle (as reported in [pub:19]) focused on the aspect of usability and user experience of the framework. Next, the second cycle collected intermediate community feedback on different conference and workshop settings (as reported in [pub:24]). Finally, the third cycle evaluated the perceived practicality, usability, and expected effectiveness of using the course planning framework with a broader audience. It also identified further areas for improvement in terms of contextualizing and using the framework in interventions and training with educators.

Each of the development cycles is described in more detail below, including the evaluations that were conducted during each cycle.

6.2.2 Development Cycles and Evaluation

Exploration and Initial Design

With the recognition that there are domain-specific AI competencies, there was a need to understand how to identify relevant AI competencies in the context of a particular domain and to support educators with a structured approach to reflect on curricular changes in their courses. While many generic course planning tools exist, it remains difficult for educators without AI expertise to analyze and identify the relevant aspects in the context of AI [78, 235]. Thus, the framework was developed out of a practical need, but integrated theoretical foundations into course planning.

Course Planning Frameworks In the background chapter (Section 2.3), several general course planning frameworks and instructional design methodologies were introduced. Examples include the *ADDIE* instructional design approach [37], Kern's six-step approach to curriculum development [145], *Understanding by Design* [330], and *Constructive Alignment* [21]. In addition, the idea of using a design tool as a practical and visual framework for lesson planning [119, url:9], lesson redesign [276], or curriculum development [334] has been tried before. The use of design tools is mostly inspired by ideas from *Design Thinking* [213] and the *Business Model Canvas* introduced by Osterwalder et al. [247].

AI Contextualization Most course design frameworks rely on identifying relevant learning outcomes based on learners' experiences and pre-existing knowledge (see Section 2.3). However, similar to other interdisciplinary course settings, learning outcomes in domain-specific AI education are also influenced by the domain. Thus, when integrating AI education into the disciplines, course developers or instructors need to specify the application areas and implications of AI in the respective domain before considering learning outcomes. In addition, learners' and instructors' requirements for experiencing and interacting with AI need to be considered.

To address this issue and to support course developers or instructors, the proposed solution extends the general idea of course planning frameworks to identify relevant learning outcomes based on learners' experiences and pre-existing knowledge to specific considerations regarding the application of AI in the respective domain. As such, the design solution develops and proposes a concise planning tool for domain-specific AI course design that aims to support educators in integrating AI competencies into their course offerings, such as entire courses or smaller content sections.

Initial Design The initial design was developed by extending traditional course planning methods to the AI context. Relevant questions from theory and practice were collected, such as the type of data in the domain, use cases, or implications. In addition, categories were created that included one aspect but one or more questions. For visualization, the categories were then placed on a visual canvas (see Figure B.8 and Figure 6.3 for examples).

Practitioner Feedback To gather feedback, the initial design was discussed with three experts with experience in designing interdisciplinary AI courses. It was also tested in a small workshop setting with teaching fellows from the AI Campus[1] in October 2022. These AI Campus teaching fellows were educators who wanted to integrate AI Campus OER materials into their courses. As they were actively developing domain-specific AI courses, while often not being AI experts themselves, they were a good initial target group. Feedback was collected in a group discussion after participants had used the framework to describe their courses. This led to the first initial design solution, which was then used in the following three cycles (see Figure B.8).

Cycle 1: Workshop Target Audience

Procedure To further test the prototype in the field and to evaluate usability and user experience, a workshop was held in November 2022 specifically for faculty and others involved in developing AI courses for non-CS students. The invitation to the two-hour online workshop was shared on social media and promoted by the AI Campus platform on its website and newsletter. No targeted advertising was used, as it was assumed that the recruitment methods described above would reach a sufficient number of representatives of the target group. Participation in the workshop was free and voluntary, and participants registered by filling out an online form. As all workshop participants were German native speakers, the workshop language was German. Of the 22 people who registered for the workshop, 18 actually attended.

The workshop was divided into three parts. The first part explained the concept of domain-specific AI education in more detail (see Section 3.2). In this context, the difference between general AI education and domain-specific AI education was explained and the framework was introduced. In the second part, participants worked in small groups without external supervision to complete the framework. The original version of the framework used in the workshop can be found in the Figure B.8. After completing each section, the results were shared with the other groups.

In the third phase, participants were asked to complete an online questionnaire that included questions about the usability and user experience of working with the framework, as well as open points for improvement. Following the iterative design-based research approach, the results and feedback from the participants were used to further improve the underlying prototype.

[1] `https://ki-campus.org/` (Last Accessed: 05.02.2025)

Evaluation Instruments Two well-known and widely used scales were applied to support the evaluation of the tool: The System Usability Scale (SUS) [42] and the User Experience Questionnaire (UEQ) [175]. In its original version, the SUS consists of ten items and was originally developed for the quick and inexpensive evaluation of industrial systems.

Since its development, however, the SUS has been used in a variety of application domains [184] and has also been used to evaluate a variety of educational technologies [316]. Because the proposed framework is not a technological system, three items were omitted (items 1, 4, and 5 from [42]). The UEQ items were presented as recommended by Laugwitz et al. [175]. In addition to the two scales, two open-ended questions were asked about features of the framework that were particularly helpful and aspects that could be improved.

Data Analysis The data were analyzed using Microsoft Excel and the automatic data analysis of the survey program. The SUS was analyzed according to the recommendations of Brooke et al. [42], which suggests first inverting the scores of the negatively worded items and then adding the average of each item. The authors [42] recommend multiplying the sum by 2.5 to convert the 0–40 scores into a composite measure of overall usability between 0 and 100, which in our case means multiplying the sum by 3.571 to account for the smaller number of items. For the evaluation of the UEQ, the average of each item was determined and presented on a semantic differential (see Figure 6.4). The responses to the open-ended questions were analyzed qualitatively. Statements that appeared similarly in the responses of different workshop participants were paraphrased and reported.

Cycle 2: Intermediate Community Feedback

The updated prototype was presented, tested, and discussed in several community events and conversations. While no data was collected because of time constraints and varying levels of interaction, it is reported here for transparency and to provide evidence of community feedback. In total, over 100 educators engaged with the framework at various levels of depth. For example, the framework was presented in the context of an online community barcamp of the Hochschulforum Digitalisierung in January 2023 [url:7] with practitioners from different fields, and in the context of AI practitioners in a talk titled "Teaching AI: A Practical Guide to integrating AI into the Curriculum" given in the context of the AI Camp of the German Informatics Society. To facilitate access for practitioners, a blog post was written and published on the AI Campus website [url:11].

The framework was also presented to 35 engineering educators in a workshop at the 51st annual conference of the European Society for Engineering Education (SEFI) in September 2023 [pub:24]. This experience highlighted the difficulty of contextualizing AI as a topic in the context of the respective disciplines. The workshop also discussed the ethical and environmental dimensions of AI.

It was also discussed in the context of European-wide computer science education with a poster presentation at the Train-DL summit in early 2024 and from an international perspective in a workshop at the Harvard Graduate School of Education in April 2024. Additionally, educators engaged with it in an one hour online workshop at the University Future Festival in June 2024 with 50 participants. Further impressions were gathered during an online talk in the AI series of the Bavarian State Institute for University Research and Planning in November 2024 and a poster presentation for young AI researchers at the AI Grid Summit in the same month.

This community feedback improved the positioning of the framework as a structural help to identify AI competencies in the context of domains. It also highlighted the challenges educators face in integrating AI as a subject. Overall, this community feedback supported the need for the framework and laid the groundwork for another evaluation cycle.

Cycle 3: Workshop Wide Range of Audience

Procedure To evaluate the practicality, usability, and expected effectiveness, another workshop was conducted in December 2024 as part of a didactic training series for a broad audience of educators. The workshop lasted three hours and was divided into four parts. First, participants received an introduction to integrating AI competencies into their courses and an overview of the framework. Second, they worked in small, randomly selected groups of two to four people, using a self-selected example, to complete the framework and note observations. They were given 35 minutes to complete this task. Third, participants were asked to share their experiences using the framework in a quantitative online survey. Of the 24 participants who interacted with the framework, 17 took this voluntary step. Fourth, participants shared their experiences in subgroups that brought together two previous groups. This allowed for further reflection on the experiences. The reflections were then collected and discussed in the plenary session.

Evaluation Instruments For the quantitative survey, the adapted SUS scale [42] was used to assess the usability of the improved version, the same as for the previous design iteration. In addition, participants were asked to report on challenges in using the framework. In addition, to assess the expected effectiveness of the framework, participants were asked to indicate their agreement with statements about the practicality of the framework, their own confidence, the outcome, perceived value, recommendations to others, and new insights, as well as its use in collaborative course design development and its ability to communicate their course ideas. The survey also included an open-ended section to collect items that were perceived as most valuable and helpful, and an open-ended section for additional suggestions.

Because the participants came from a wide range of disciplines, experience levels, and expectations, a group discussion was initiated to further contextualize the observations and quantitative data. In the group discussion, participants actively took notes using an online collaborative board. Key themes were identified and discussed in the smaller groups. In addition, the concept board that the groups worked on was analyzed to understand the interaction with the framework.

Data Analysis The quantitative data was analyzed using Microsoft Excel. To calculate the SUS score, the procedure proposed by Brooke et al. [42] was followed, including inverting negatively worded items, summing the average over all items, and accounting for the smaller number of items (see Design Cycle 1). The other items were analyzed separately in a descriptive form by calculating the mean, standard deviation, and range. Responses to the open-ended questions were analyzed qualitatively by forming constructs. Notes from the group discussion were consolidated into themes. In addition, the outcomes of the group work were analyzed concerning domains, completeness, and content.

6.3 AI Course Design Planning Framework

Figure 6.3 shows a graphical presentation of the AI Course Design Planning Framework as a concise course development tool[2]. The framework consists of three interacting pillars, namely *AI in the domain*, *learning environment*, and *course implementation*. The first pillar AI in the domain focuses on the external context of the application of AI in the context of a domain, such as use cases, data, or implications of AI use. The second pillar reflects the learning environment in which the course takes place, such as the learners and their interaction with the AI, the instructor's competencies, and the available internal support. The third pillar describes the course implementation with learning outcomes, assessment, and learning activities, all supported by the findings from the previous two pillars. Thus, the first two pillars

[2] A blank version of the canvas is available for download at [url:12] and can be used under open license.

have a supporting function. They can be interpreted in terms of Kern's six-step approach [145] as the *needs assessment* component that serves as the basis for the pedagogical structure of the course. The following describes the framework from left to right and explains its intended use in the context of domain-specific AI education.

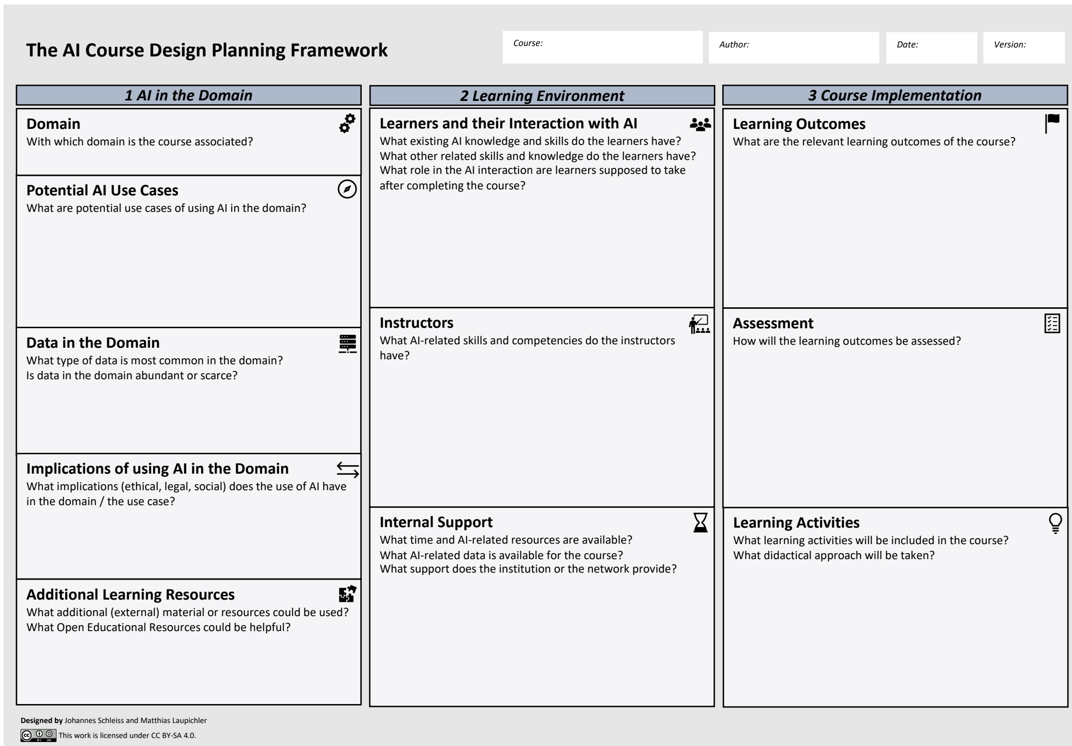

Figure 6.3: The AI Course Design Planning Framework with its three pillars focusing on (1) AI in the domain, (2) the learning environment, and (3) the course implementation.

6.3.1 AI in the Domain

Describing the use of AI in the domain is the starting point for any effort to create a domain-specific AI course, as it determines what content will be taught in the corresponding courses. The subtopics of this pillar are presented in the following subsections.

Domain

The term domain is used to refer to the discipline in which AI is to be applied. For AI applications in medicine, an exemplary domain could be "radiology", and for AI applications in automotive engineering, it could be "mechanical engineering".

Potential AI Use Cases in the Domain

This subtopic focuses on the impact of AI technology in the domain. It helps to structure the issues that will be relevant to students and learners in the near future. Its goal is to support the identification of current use cases and the prognostic assessment of possible future use cases in which AI could play a role in solving domain-specific problems. Taking the example of radiology, a typical example could be AI-based image analysis such as segmentation of anatomical structures or detection of abnormalities in images [122]. In the mechanical engineering example, an example might be predictive maintenance, which is the prediction of machine failure or the need for maintenance based on sensor data [67].

Data in the Domain

The identified AI use cases are usually based on the most relevant type of data in the domain. The subtopic is not about which data is easy to get or how it can be used, but rather about the type of data. Knowing the typical data in a given domain enables more targeted use of AI techniques and specification of the data. It makes a big difference for the AI techniques to be taught whether the domain mainly works with time series data, text, images, or other types of data. It is also an important consideration whether the data in the domain is abundant or scarce.

Implications of Using AI in the Domain

Another important factor to consider is the potential implications of using AI in the domain [32]. This mainly concerns ethical, legal and social implications [61, 207]. Societal and ethical issues should not be isolated, as they are directly related and intertwined with the context of the application of AI [78]. For example, using AI to support medical triage decisions has different implications than using it to optimize energy consumption in a manufacturing plant. Understanding the impact of technology on their domain helps students adhere to societal and ethical standards when using or developing AI technologies in their domain.

Additional Learning Resources

The creation of course materials can be supported and guided by existing learning materials and by oneself, colleagues, or other institutions. In particular, OER can provide a basis for course development and can be used as preparatory or supplementary materials in course design [pub:10, pub:16, 333].

Overall, the answers to the questions in this pillar form the basis for the skills and knowledge to be taught in the course units.

6.3.2 Learning Environment

In addition to the external aspects of AI in the domain (Section 6.3.1), there are several ways in which the learning environment in which the course takes place can influence the pedagogical implementation of the course. At the same time, the framework can also be used to develop not a whole course offering, but only a part of it, as in a week of content on AI. As interdisciplinary courses, domain-specific AI courses place special demands on learners, instructors, and internal support. It is therefore important to fully understand who the learners are, what skills the instructor has, and what additional internal support is available.

Learners and Their Interaction with AI

Regarding learners, three considerations are important for domain-specific AI courses. First, it is important to understand what AI skills and related competencies, such as mathematical foundations, computational literacy, data literacy, or programming skills, learners have already acquired. Second, it is important to clarify the role of the group of learners in their interaction with AI in order to select relevant demonstrations of AI applications and an appropriate level of difficulty. One example to describe the role can be the taxonomy proposed by Faruqe et al. [87], which presents four groups whose frequency of contact with AI and AI competency requirements differ from each other. According to the authors, the levels in ascending order are *Consumers, the General Public and Policymakers, Co-Workers and Users of AI Products, Collaborators and AI Implementers*, and *Creators of AI* [87]. Third, the existing competencies and the future role are influenced by the curricular integration of the course into an overall program. In addition, the curricular integration determines whether the course is a required course and, if so, the expected number of students in the course. Note that depending on the interdisciplinarity of the course, the group of learners may be more heterogeneous, with students from different fields and with different experiences. Therefore, the contextualization of the environment in which the course takes place is relevant for defining the course implementation.

Instructors

In addition to learners, instructors or educators play an important role in the learning process [142]. Domain-specific AI teaching requires a mix of sufficient AI knowledge, domain expertise, and pedagogical skills to teach an interdisciplinary course, as well as the motivation and time from an instructor's perspective. The AI knowledge of faculty and instructors tends to be quite heterogeneous, ranging from no previous AI experience to decades of AI research experience [235]. Therefore, it is important to understand and assess the instructor's ability to teach the course. However, when instructors self-assess their knowledge and skills in AI, attention must be paid to possible cognitive biases or heuristics that lead to an under- or overestimation of actual AI skills. In several other professional contexts, it has been found that people relatively rarely assess their skills correctly and it can be assumed that it is no different when assessing one's own AI knowledge and skills [68, 165].

Internal Support

Internal support, such as budget, staffing constraints, maximum course length, available data, software, and hardware, can be viewed as resources in a positive sense or as constraints in a negative sense. In the context of teaching AI, two important considerations are the availability of data and the availability of hardware and computing resources. In addition, instructor support (e.g., through training), institutional barriers to interdisciplinary teaching, and student support (e.g., through additional resources and infrastructure) play a role in the design of an interdisciplinary course [312].

6.3.3 Course Implementation

The right pillar represents the core of the framework, as it combines the insights from the previous pillars. It aims to create a pedagogical structure that can be interpreted as an abbreviated version of the final course implementation. The pillar is structured according to the Constructive Alignment approach [21], which aligns the desired learning outcomes, the assessment of those outcomes, and the corresponding learning activities.

Learning Outcomes

Defining the content and scope of learning outcomes is an important building block in the context of domain-specific AI instruction, informed by the considerations of the other pillars and determining the focus of the course. To organize learning outcomes in a structured, consistent, and verifiable way, it is recommended to formulate learning objectives [21]. Learning objectives should be specific, measurable, achievable, reasonable, and time-bound (i.e., "SMART" objectives; [75]) whenever possible. They should also focus on specific levels of competencies according to Bloom's Taxonomy [162]. The course learning objectives determine the structure of the course and indicate the time and resources that will be spent on each topic. The learning objectives should be shared with students so that they know which aspects of the course are most relevant to their professional development.

Assessment

Following the Constructive Alignment approach, it is important to consider in advance the methods and ways in which learning objectives will be assessed [21]. Assessment in interdisciplinary courses requires a balance between the experiences of different groups of learners and the desired outcome in terms of their interaction with AI. In addition to traditional assessment methods such as exams, tests, oral presentations, or reports, the applied nature of domain-specific AI education can benefit from project- or problem-based assessments that are linked to real-world applications (see [342] for an example). In addition, research in interdisciplinary education suggests that using assessment through reflection can help students bridge disciplinary silos [312]. As in other fields, the use of different assessment components can be a useful and fair approach to take into account the different experiences of students from different disciplines [133].

Learning Activities

The final step focuses on the learning activities that lead to the desired learning objectives [21]. Thus, the focus is on the pedagogical implementation of the overall course design. In this context, the Merrill Principles of Learning [214] should be considered to promote an effective learning experience. Experience from the few domain-specific AI courses that are being taught today shows that a combination of different teaching methods is often used to address the different aspects of AI [341]. The overview of learning activities provides the basis for more detailed planning of learning activities throughout the course. This may include the use of AI-based learning activities (cf. Section 3.3).

6.3.4 Intended Use of the AI Course Design Planning Framework

After describing the pillars of the framework and their underlying categories, this section briefly explains the intended use in the context of course development for domain-specific AI courses. The AI Course Design Planning Framework is a visual and practical tool for instructors and course developers in higher education or professional training contexts, with a particular focus on non-computer science (non-CS) students. It can be used as a means to brainstorm, innovate, plan, and communicate ideas for domain-specific AI courses. The framework can be used as a stand-alone tool for individuals, in tandem with AI and domain experts in a multi-person workshop setting. It is suggested to be filled from left to right: first considering the questions about AI in the domain, then the learning environment of the course, and finally the course implementation.

For reference and further explanation, two completed examples of AI courses in mechanical engineering (Figure B.6) and radiology (Figure B.7) can be found in the Appendix B.4.1.

6.4 Evaluation

6.4.1 Cycle 1: Usability and User Experience

Participants

Of the 18 workshop participants, twelve (66%) completed the questionnaire. To understand how the sample of participants reflects the generalizability of the findings, background, occupation, and self-reported AI expertise were assessed. Three participants indicated that they were from the field of AI education, three were from the field of medicine, two were educational psychologists, two were from the field of organizational and university development, and one person was associated with the life sciences. When asked about their occupation, six participants (50%) said they worked at a university of applied sciences, five (42%) worked at a university, and one person was from another educational institution. The level of AI expertise also varied widely among the participants. While some participants had either already developed AI applications or conducted AI research (n=3, 25%) or had been involved with AI for a long time (n=2, 16%), four participants (33%) reported having a good understanding of AI, and three (25%) had only a rough idea of how AI works.

Usability

All participants completed all items from both the SUS and UEQ. All SUS items were recoded according to the instructions of Brooke et al. [42]. After adding the average of all seven items, the sum was multiplied by 3.571 to obtain the final SUS score. The resulting items are presented in Table 6.1. The final score was 81.2, which, according to the item benchmarks presented by Lewis et al. [184], corresponds to an “A” (A+ to

F grading system) and is in the 90th to 95th percentile. Thus, the scores indicate a very good perceived usability when using the framework.

Table 6.1: Descriptive statistics for the SUS items for evaluation cycle 1 with mean, standard deviation (SD) and range (R). Items with negative connotations are marked −.

SUS-Item	Mean	SD	R
I found the system unnecessarily complex. (−)	2.0	1.1	4
I thought the system was easy to use.	4.3	0.4	1
I thought there was too much inconsistency in this system. (−)	1.9	0.8	2
I would imagine that most people would learn to use this system very quickly.	4.7	0.5	1
I found the system very cumbersome to use. (−)	1.8	0.9	3
I felt very confident using the system.	3.9	0.6	2
I needed to learn a lot of things before I could get going with this system. (−)	1.4	0.6	2

User Experience

On average, the participants rated the attractiveness of the AI Course Design Planning Framework in the first iteration with 1.43 on a scale of −3 to +3 (standard deviation (SD) = 0.89, 95% Confidence Interval (CI) [0.93, 1.94]). When compared to a benchmark [277], this can be interpreted as *above average*. Perspicuity was rated with 2.02 (SD = 0.80, 95 % CI [1.57, 2.48]; *excellent*), efficiency with 1.94 (SD = 0.64, 95 % CI [1.58, 2.30]; *excellent*), dependability with 1.56 (SD = 1.02, 95% CI [0.98, 2.14]; *good*), stimulation with 1.21 (SD = 1.10, 95% CI [0.59, 1.83]; *above average*) and novelty with 0.08 (SD = 0.99, 95% CI [−0.48, 0.64]; *bad*). The average UEQ scores per item are shown in Figure 6.4.

Qualitative Responses

In identifying aspects for improvement, many of the workshop participants praised the structuring possibilities offered by the AI Course Design Planning Framework. For example, seven participants appreciated the ability to use the framework to conduct structured development and evaluation of AI courses. In addition, three participants liked the questions in the individual text boxes that support the concretization of course development projects. One participant pointed out the possibility of using the framework to reflect on one's own (institutional) situation in relation to AI education. Beyond supporting concrete course development, one participant pointed to the possibility of using the framework to organize and evaluate the more abstract development of entire AI curricula.

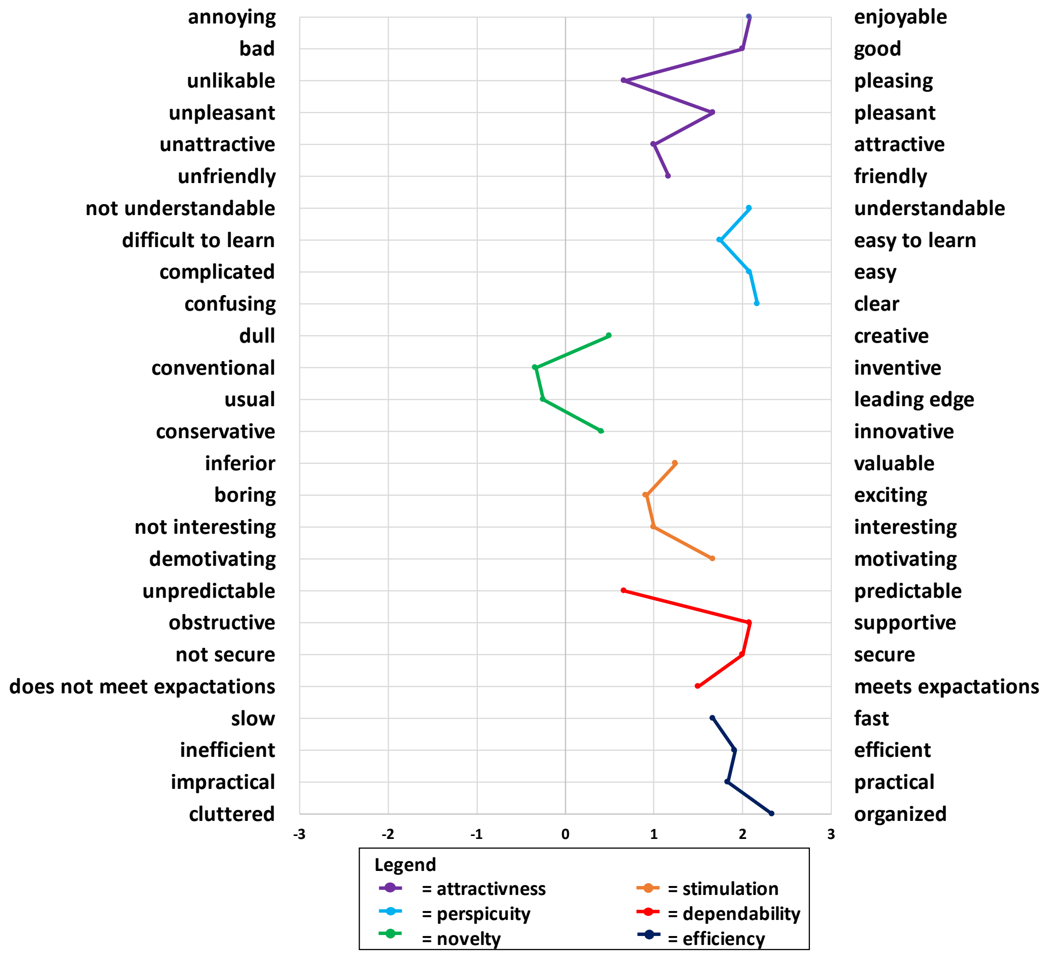

Figure 6.4: User Experience Questionnaire scores for AI Course Design Planning Framework with the average score on a scale of -3 to +3 for each UEQ item. The individual UEQ subcategories *attractiveness*, *perspicuity*, *novelty*, *stimulation*, *dependability*, and *efficiency* are separated by color.

The open-ended qualitative questions also asked for suggestions for improving the framework used in the workshop (Figure B.8). In this context, four participants expressed a desire for more detailed explanations of the individual areas of the framework and their interrelationships. In addition, two participants made recommendations on how to improve the layout of the questionnaire to make it easier to understand. One participant suggested that users of the framework should be provided with tips on tools that might facilitate the application of the framework. Finally, one participant requested that more attention be paid to the potential transfer of internal factors.

In response to the question “Is there something missing from this framework?”, design and layout aspects were mentioned. For example, several people indicated that the questions in the corresponding boxes (see Figure B.8) were too general and did not fit some domains. In addition, some participants wished for a better explanation of the framework, for example by numbering the pillars or by providing short explanations on how to complete them.

These considerations were used to improve the framework to the version presented in Section 6.3. Modifications to the prototype based on participants’ feedback are summarized in Table B.2.

6.4.2 Cycle 2: Community Feedback

Community feedback has not been collected in a standardized form or data collection method, mostly because of time constraints in each setting and limited opportunities for deeper interaction with the framework. However, discussions at conferences, poster presentations, and smaller workshop formats provided cumulative feedback on usage and the challenges educators face. For example, in the workshop held at the SEFI conference with 35 engineering educators (reported in [pub:24]), the following observations, experiences, and difficulties in working with the framework were identified. First, several groups had difficulty defining potential AI use cases in the context of their domain, some of which was because of a lack of knowledge and skills in industrial AI from the educators’ perspective. This was also supported by the observation that four out of six teams used use cases involving large language models, which could be classified more as consumer AI. Some participants emphasized that they would have found it helpful to build on existing use cases and examples. Second, scoping learners’ skills and backgrounds was perceived as challenging, especially from an AI perspective. For the most part, it was unclear to educators how much students were using consumer AI, for example, and what they could learn from it. Correspondingly, there was not always insight into instructor competencies, especially in larger course settings with multiple instructors. Finally, one group discussed the category of impact of using AI in the field, mentioning that environmental impact could be an addition. Overall, participants emphasized the simplicity of the framework and that it allows for rapid iteration in course development, especially in the early stages of development. They also found it easy to work with the right part of the canvas, which corresponds to classic course design frameworks.

In the different experiences of presenting the framework, these exemplary observations came back in different forms, depending on the audience and the level of AI competencies. It was therefore important to test the use of the framework with another audience in order to determine how it needed to be further contextualized.

6.4.3 Cycle 3: Broad Audience Interaction

Compared to the previous cycles, this cycle had a broad audience, as it was promoted through a series of didactic trainings. Moreover, it is important to note that the data was collected at a time when generative AI was on the minds of educators, and most of the concerns and efforts were going into using generative AI in the context of teaching and learning.

Participants

Of the 24 people who interacted with the canvas in the workshop phase, 17 participants (71%) participated in the survey. As indicated in Table 6.2, the participant statistics reflect a wide variety of experiences and domains. While the participants had solid teaching experience, with 53% having taught for more than ten years, their experience with AI was quite diverse. Most participants reported using AI tools occasionally (24%) or frequently (35%) in their personal lives. At the same time, 24% had never participated in AI training and 18% rarely, and 47% had never used AI for research. In addition, 47% had never taught an AI course, and 41% said that this was the first time they had thought about teaching an AI course in their field. Overall, this suggests that the sample was relatively broad and may not be a good fit for the target audience of the framework. As such, the data should be interpreted with caution and taken as preliminary findings rather than definitive evidence.

Table 6.2: Characteristics of the participants of cycle 3 workshop with N referring to the number of persons choosing this response option and % as the percentage of the response option in the total sample.

Response Options	**N**	**%**
Domain of Expertise		
Technology and IT	0	0%
Healthcare	3	18%
Finance and Economics	0	0%
Education	3	18%
Science	1	6%
Engineering	1	6%

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Table 6.2 – continued from previous page

Response Options	**N**	**%**
Business and Management	1	6%
Arts and Humanities	2	12%
Legal	0	0%
Environment and Sustainability	0	0%
Social Sciences	2	12%
Other	3	18%
No Answer	1	6%
Overall Teaching Experience		
I have taught courses in a formal educational setting.		
No	1	6%
Few (1-2)	1	6%
Some (3-5)	2	12%
Many (5-10)	3	18%
A lot (10+)	9	53%
No Answer	1	6%
I have taken formal didactic/teaching training.		
No	3	18%
Few (1-2)	0	0%
Some (3-5)	3	18%
Many (5-10)	1	6%
A lot (10+)	8	47%
No Answer	2	12%
Experience with AI		
I have used AI in my personal life.		
Never (0 times)	0	0%
Rarely (1-3 times)	3	18%
Occasionally (4-7 times)	4	24%
Frequently (7-15 times)	6	35%
Always (15+)	3	18%
No Answer	1	6%
I have participated in training on AI.		
Never (0 times)	4	24%
Rarely (1-3 times)	3	18%
Occasionally (4-7 times)	3	18%
Frequently (7-15 times)	6	35%
Always (15+)	0	0%
No Answer	1	6%
I have used AI in research.		
Never (0 times)	8	47%
Rarely (1-3 times)	3	18%
Occasionally (4-7 times)	2	12%
Frequently (7-15 times)	2	12%
Always (15+)	1	6%

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Table 6.2 – continued from previous page

Response Options	N	%
No Answer	1	6%
I have taught AI courses.		
Never (0 times)	8	47%
Rarely (1-3 times)	3	18%
Occasionally (4-7 times)	4	24%
Frequently (7-15 times)	1	6%
Always (15+)	0	0%
No Answer	1	6%
Experience Level with AI courses		
It was my first time thinking about an AI course in my domain.	7	41%
I have thought about developing an AI course in my domain.	2	12%
I have already developed a clear plan for an AI course in my domain but have not started to teach it yet.	2	12%
I am already teaching AI in the context of my domain.	4	24%
No Answer	2	12%

Usability

Table 6.3 shows the results of the SUS items of evaluation cycle 3 with the respective mean, standard deviation, and range. Overall, the data indicates a generally positive usability. Compared to the evaluation cycle 1, however, there was no agreement that the system was easy to use, and participants also did not feel confident in using the system while disagreeing that they needed to learn a lot of things before they could get going and have a slight agreement that most people would learn to use the system very quickly. Moreover, the standard deviations indicate a range of variance in experiences and perceived usability.

Table 6.3: Descriptive statistics for the SUS items of evaluation cycle 3 with mean, standard deviation (SD), and range (R). Items with negative connotations are marked −.

SUS-Item	Mean	SD	R
I found the system unnecessarily complex. (−)	1.4	0.9	3
I thought the system was easy to use.	1.9	1.1	3
I thought there was too much inconsistency in this system. (−)	1.9	1.0	3
I would imagine that most people would learn to use this system very quickly.	2.5	1.1	3
I found the system very cumbersome to use. (−)	1.3	1.1	3
I felt very confident using the system.	1.8	1.1	4
I needed to learn a lot of things before I could get going with this system. (−)	1.4	0.9	3

Practicality

Table 6.4 provided some further insight into the perception of the broader audience. The overall perception was rather negative, with participants slightly disagreeing with the statement that the framework helped them to develop and plan their course and that it added value to their usual design process. Again, however, the range and standard deviation indicate a relatively high variance in the data points.

Table 6.4: Evaluation of the course development framework in cycle 3 with mean, standard deviation (SD), and range (R).

Statement	Mean	SD	R
The framework helped me in developing and planning my course.	1.6	1.2	4
I feel confident in filling the framework when new AI technologies arise.	2.5	1.3	4
The idea of my course is represented through the framework.	2.0	1.2	4
The framework added value compared to my usual course design process.	1.8	1.2	4
I would recommend the use of the framework to a colleague.	2.2	1.4	4
The framework can facilitate collaborative course design development (e.g., with other educators or students).	2.6	1.2	4
The framework helps me communicate my ideas to others (e.g., other educators or students).	2.5	1.3	4
Filling the framework provided me with new insights.	2.1	1.1	4

Qualitative Responses

Encountered Challenges To further contextualize the data, participants were also able to leave open-ended comments about challenges they encountered. Participants mentioned the perception that the framework does not fit their discipline (2), for example in the context of teacher education. In addition, unclear points were addressed in filling out the framework (5), for example related to use cases in the domain. Three participants also stated that a lack of experience in AI hinders them in filling out the framework. In addition, four statements indicated a misconception of the framework, expecting it was designed to identify use cases for AI in education. Finally, two comments related to the workshop setting, highlighting that the diversity of people was difficult to work with.

Perceived Value Participants had the opportunity to note which points were most valuable and helpful to them. Two comments related to overview and structure, e.g., that the framework allowed for an initial overview before going deeper into planning. In addition, one comment referred to the value of identifying commonalities for AI education in a group setting.

Further Suggestions In terms of final comments, improvements, and suggestions, two people mentioned the need for more input, two people highlighted the need for an example framework, one person added that more reflection in the context of assessment could be useful, and two people wished for more contextualization towards AI in education.

Group Discussion

After completing the survey, workshop participants engaged in a group discussion to reflect their experiences with the framework, which helped to further contextualize the quantitative data. In this context, it became clear that some participants had expected or focused on using AI in an educational context rather than teaching about it. For example, one participant highlighted the difficulty of focus on training about AI vs. expectation of learning/teaching with AI. The majority of participants therefore misinterpreted the use of the framework, even though it had been introduced earlier in a 30-minute input and they had signed up for a workshop that stated that it was about a design framework for designing AI courses. In addition, participants felt that they lacked the AI competencies to fill out the framework or to plan for integrating AI content into their modules. For example, one group noted in their reflection: *"In our group, we are not yet ready to set up an AI-specific course for students. To do this, we first need to acquire or differentiate our own AI competencies."* Finally, participants highlighted the difficulty of working on this topic in cross-disciplinary groups (the groups were selected randomly rather than discipline-specifically).

Analysis of Group Outcomes

After the workshops, the results of the group work were analyzed based on the online work board in which the participants participated. A total of nine groups were analyzed.

Diversity of Domains The groups represented a wide range of academic fields, highlighting the adaptability of the framework to different domains. Overall, there were three groups for health and medicine, three groups for education (e.g., teacher training), and one each for engineering, business, and media. However, some disciplines (e.g., STEM-focused fields like engineering or healthcare) had more detailed and specific use cases compared to others (e.g., education and teaching).

Data Completeness The level of completeness varied across the groups, with some columns well populated with detailed information, while others were sparsely populated or missing altogether (likely also because of time constraints). Overall, three sparsely filled categories were *external learning resources*, *internal support*, and *assessments*. For example, only a few groups mentioned external resources, suggesting either limited awareness of available resources or insufficient focus on integrating external materials. Similarly, few groups had explicitly considered how AI-related learning would be assessed, which could indicate either difficulties in designing AI-related assessments or a lack of focus on this area during the planning phase.

Ethical and Legal Concerns Many groups highlighted issues such as privacy, bias, authorship, and copyright in the context of *implications*. In addition, a strong focus on teaching students to critically evaluate AI results and to use AI ethically could be seen throughout the *learning outcomes*.

Levels of AI Competencies Groups often mentioned the heterogeneity of AI competencies among both students and educators, with one group stating *"Problem: students often know more than educators"*.

Focus on Generative AI Several groups highlighted the importance of teaching students how to interact effectively with AI tools through prompts, suggesting a focus on generative AI and LLMs rather than other AI approaches. This was also reflected in the identified *AI use cases in the domain* category, which does not include a variety of relevant use cases per domain and a focus on generative AI tools. Moreover, this category seemed to be interpreted in a course-specific way, rather than reflecting AI use cases in the domain at large.

6.5 Discussion

This chapter described the development and evaluation of an AI Course Design Planning Framework as a tool for developing domain-specific AI courses for non-CS students, which was evaluated by participants in two online workshops and through several community events.

6.5.1 Main Findings

How can a structured framework effectively support educators in developing domain-specific AI courses?

The goal of this chapter was to support educators in developing domain-specific AI courses by providing a structured approach that simplifies the complexity of integrating AI competencies into domains. Using the collected data and observations from the three design cycles, two themes were identified that help support educators with a structured framework.

Structure and Iteration Overall, the structure of the framework allowed educators to organize their ideas and reflections in a systematic way. For example, cycle 1 participants commented positively on the framework's ability to structure development processes. In addition, the rapid iteration in the early stages of course development was highlighted as a strength, emphasizing flexibility and adaptability, including to new technological developments.

Reflection and Collaboration The framework's structured categories and questions encouraged participants to reflect on their domain's needs and potential AI use cases. In the design iterations, it was mostly tested in a collaborative environment, which led to different experiences. The most recent evaluation in cycle 3 showed that participants found it difficult to contextualize teaching about AI in their domain, especially when working in a cross-disciplinary group. Therefore, the framework should be used in a disciplinary group setting to potentially allow people with more experience to lead the discussion.

How do instructors perceive the usability and user experience of the course planning framework in the context of developing domain-specific AI courses?

Instructors' perceptions of the usability and user experience of the framework varied across different evaluation cycles, highlighting both strengths and challenges.

Positive Perceptions In cycle 1, instructors rated the framework highly in terms of usability and the user experience. The SUS score of 81.2 placed it in the 90th-95th percentile, equivalent to an A grade. Similarly, the UEQ showed favorable ratings in categories such as perspicuity (clarity and understandability) and efficiency (speed and ease of use). These results suggest that the framework is intuitive and accessible to educators with moderate to high levels of AI expertise.

User experience, as tested in cycle 1, showed that subcategories such as perspicuity (rated 2.02, *excellent*) and efficiency (rated 1.94) were particularly strong, indicating that educators found the framework clear and quick to use. However, novelty received a low rating (0.08, *bad*), suggesting that the framework lacked innovative or surprising elements. This may partly explain why some educators felt that it added little value to their usual course design process in cycle 3.

Challenges with Broader Audiences In cycle 3, perceptions of usability were more mixed. Although participants still found the framework simple and useful in its core structure, they reported less confidence in using it. For example, the SUS score was lower, and participants disagreed that the system was “easy to use” or that they felt confident using it. The broader audience in cycle 3 had diverse backgrounds and less AI expertise, which likely contributed to these challenges. In addition, the group discussions in cycle 3 revealed that some educators misunderstood the purpose of the framework, confusing it with a tool for integrating AI into the classroom rather than facilitating curricular changes to include education about AI. This suggests the need for a clearer framework and targeted interventions that support educators in first reflecting on or exploring AI use cases in the context of their domain, and then filling in the framework.

Teaching and Learning with AI vs. about AI As the first workshop was conducted in November 2022, before the emergence of generative AI in education, the results of the collected data points differ, with aspects such as initial expectations and conceptualizations changing significantly over time. Compared to November 2022, the workshop participants in December 2024 were more exposed to the topic of AI, especially in the context of reacting to the use of LLMs in learning. In particular, the quantitative data and group discussion in the December 2024 workshop, as well as the community feedback in cycle 2, indicated that the current focus, interest, and expectation of educators is to learn about the use of AI in educational scenarios rather than to teach about AI. For example, although the workshop description in cycle 3 clearly indicated that the workshop was about designing AI courses and was broadly introduced in the workshop, the participants’ concerns were about teaching and learning with AI rather than about AI. Therefore, the quantitative data collected in cycle 3 should not be over-interpreted, as the contextual data and group discussions indicate misinterpretations of the use of the framework as well as false expectations about it, both of which were not assessed in the quantitative data collection. These findings also suggest that the framework may need to be further contextualized with additional input on identifying use cases in the field or an exercise to discuss the use of AI in workplace scenarios rather than learning scenarios.

Educators’ AI Competencies The data from cycle 3, as well as the impressions from cycle 2, also support the hypothesis that, to date, most educators do not feel confident enough in their own AI competencies to reflect the use cases of AI in the realities of their disciplines and, therefore, to change learning objectives or content. The range of AI experiences and expectations may also be related to the high standard deviations in the SUS items and practicality scores. However, to date, there is no reported evidence of educators’ willingness to make curriculum changes in light of AI. For the designed solution, the lack of competencies also means that the framework cannot currently be used on its own without providing further context or examples, or even a basis for using AI in the context of specific domains. As noted above, based on current observations and data, educators need to first explore the use of AI (beyond LLMs) in the context of their domains and then use the framework to reflect on and develop course offerings.

In summary, educators found the framework generally usable and effective, especially when they had prior knowledge of AI and clear guidance. However, the mixed feedback in broader contexts highlights the need for better scaffolding, more domain-specific examples, and clearer communication to support diverse educators.

6.5.2 Limitations

The study has several limitations that should be considered when interpreting the results and that could be addressed in future research. First, while a total of over 100 educators engaged with the framework, the sample size for detailed analysis remains small, with 12 subjects in the first workshop in cycle 1 and 17 subjects in the workshop in cycle 2. However, given that AI education does not involve all educators, this is still a valid development, but not yet representative evidence of the framework. In addition, the differences in perceptions and outcomes over the two years of development indicate that since the launch of ChatGPT in November 2022 and the associated AI hype in education, more educators in different fields are engaging with the topic of AI. In this context the rsults of cycle 3 show that more research is needed to understand perceptions and needs across different domains and experience levels. At the same time, the development process still has significant validity now and can be considered valuable for research.

Second, the workshop language in cycles 1 and 3 was German, and the original framework was presented in German. While the framework was used in English on several occasions in Cycle 2, there is a possibility that the translation of the materials into English could have affected the validity of the study. To address this limitation, a further validation study using the English version of the framework is necessary.

Third, the use of the framework and also perceived usability and practicality is a construct that is related to several other constructs such as participants' expectations, knowledge, beliefs, and experiences with AI [172], which could not all be considered in the methodological approach. This limitation was partially addressed by using different data collection methods and triangulating the results. However, future work could address the relationship between educators' experience or AI competencies and their perception and ability to develop curricular changes.

Finally, the evaluation focused on the usability and user experience of the framework without examining the implementation of a course using the framework. While such an endeavor would add great value to the body of knowledge and is intended to be realized in future research projects, the implementation aspect was beyond the scope of this work.

6.5.3 Implications and Future Directions

The data have several implications for the development and implementation of the course planning framework.

Improving the Intervention for Different Target Audiences First, the observations across the development cycles underscore the importance of contextualizing the framework to the specific needs and experiences of educators, particularly linking the discourse between curricular and methodological changes. This may involve providing additional support and resources to develop educators' competencies in AI, as well as further introduction to the purpose and scope of the framework. For example, in a workshop setting, it might be beneficial to first conduct an exercise to develop an understanding of AI competencies in the context of a domain and to shift the focus away from the use of AI in teaching and learning processes before using the framework.

Developing an Online Repository of Examples The data also indicated a need for examples and inspiration on how others are structuring their courses. This could be achieved by developing an online repository of populated frameworks that demonstrate how AI is taught in different domains. Such an online repository would not only provide educators with a range of examples and inspiration, but would also facilitate a community-driven approach to course design, allowing educators to learn from and build on each other's experiences. This ties into the idea of OER, particularly the 5Rs of reuse, revise, remix, redistribute, and retain [333]. In addition, a collection of course designs would provide a rich database to facilitate further research on how AI is taught in the context of different domains.

Providing Automated Support and Recommendations through LLMs Another direction could be to facilitate use by providing educators with automated support and recommendations through LLMs. This could be achieved by fine-tuning two targeted generative large language models: A *generator model* responsible for generating course outlines based on instructor input and framework specifications, and an *evaluator model* responsible for evaluating course outlines and providing constructive criticism on areas for improvement. If properly contextualized, this could support educators in the reflection process by starting with a draft rather than a blank page, similar to providing existing examples.

Connection to Examples of AI Competencies The experiences in the design cycles also indicated the need to have examples or work with existing sets of relevant competencies for students. This is related to the identification of domain-specific AI competencies as described in Chapter 4 for the case of engineering education. Thus, creating a learning catalog of AI-related competencies within specific domains and roles would be a valuable endeavor [255, pub:19]. This catalog could draw on existing frameworks such as the ESCO [70] or other frameworks for AI competencies across domains [11, 255, 270, pub:12]. These competencies could then provide a foundation in the context of learning outcomes in the course design planning framework.

Exploring the Role of OER to Support Non-Expert Educators Another direction could be to explore the role of integrating external materials, such as OER, into AI education. Particularly in a context where educators are not experts themselves and find it difficult to keep up with developments, OER can meet the needs of educators and address a wide range of learning profiles [pub:10, 270, pub:16, 333]. However, more research is needed on the use of OERs for educators who are not AI experts themselves.

6.6 Summary

Addressing the context of educators and courses, this chapter focused on the overarching question of *how educators can be supported in integrating domain-specific AI competencies into their courses.* In particular, it proposed the AI Course Design Planning Framework as a structured approach to integrating AI competencies into domain-specific education. Developed over three design iterations using a design-based research approach, the framework was shown to support educators in the initial conceptualization of curricular changes to integrate AI topics. During development, over 100 educators interacted with the framework, while two groups of 12 and 17 educators participated in a detailed controlled evaluation.

Overall, the framework is perceived as a valuable tool for educators. However, the feedback highlights the need for improved scaffolding, domain-specific examples, and clearer guidelines to help a broader range of educators use the framework effectively. In addition, experience with the framework in workshops has shown an increased focus on generative AI, particularly LLMs, over the past two years, as well as a focus by educators on methodological issues other than curricular ones.

7 Discussion and Conclusion

This dissertation aimed to contribute to multiple levels of curriculum innovation and scholarship in the field of AI education and engineering education. Previous studies highlighted research gaps in learning about AI (cf. Section 3.3), particularly in engineering education, and a gap in scholarship on curriculum change towards AI [31, 57, 94]. This led to the overarching research questions in the conceptualization and operationalization of domain-specific AI competencies at the program and course level. Specifically, the dissertation, first, targeted the overarching question of *how to conceptualize domain-specific AI competencies in the application domain of engineering*. Second, it addressed the question of *how to develop and evaluate an interdisciplinary AI curriculum for engineering*. Finally, it focused on the overarching question of *how educators can be supported in integrating domain-specific AI competencies into their courses*.

In the following, Section 7.1 first summarizes and contextualizes the work within broader research streams. Then, Section 7.2 highlights the key contributions and implications for practice. Next, Section 7.3 makes recommendations to various stakeholders. Finally, Section 7.4 discusses limitations of the work and future research directions.

7.1 Summary and Overarching Discussion

The first two chapters laid the foundation for the thesis by introducing the research gaps and the main research contexts of AI competencies, AI curriculum development, and AI course development (cf. Chapter 1). In addition, Chapter 2 introduced the underlying concepts and educational foundations, including a perspective on curriculum development and evaluation, and supporting educators in instructional design.

Chapter 3 highlighted the complexity of making curricular changes in educational systems and how they are influenced by external, internal, and individual factors (Section 3.1). From the systems perspective and the previous literature work, the chapter identified the main challenges of integrating AI competencies into engineering education, namely conceptualizing and operationalizing domain-specific AI competencies, empowering educators, benchmarking, and measuring effects (cf. Section 3.1.5). Regarding the conceptualization challenge, Section 3.2 discussed the holistic conceptualization of AI competencies along generic, domain-specific, expert, and ethics-related AI competencies. This theoretical framework allowed to highlight previous research along this conceptualization and to identify the need for further research in the definition of domain-specific AI competencies that are anchored in the domain context (cf. Section 3.2.7).

Regarding the challenge of operationalization, Section 3.3 provided an overview of reference AI curricula and implementation examples, as well as an overview on teaching and learning about and with AI. Previous research conducted in this area, highlighted the need for further research to develop novel curricular approaches at the program and course level (cf. Section 3.3). Finally, focusing on the challenge of empowerment of educators, Section 3.4 emphasized the two perspectives that educators face in adapting to teaching and learning with AI and changing their content in light of AI. Overall, Chapter 3 contextualized the challenges and empirical contributions of the work, which are further highlighted below.

Chapter 4 provided a conceptualization of domain-specific AI competencies for engineering. While previous research has focused on conceptualizing generic AI competencies [8, 177, 234], the chapter aimed to conceptualize AI competencies from a domain-specific and bottom-up perspective, contributing to the discourse on providing a holistic view of AI competencies [8, 153, 255]. Based on literature and interviews with eleven practitioners, the chapter first developed competency clusters along professional, methodological, social, and self-competences. From these, competency statements were formed and validated with a quantitative survey of a panel of 32 experts from industry and academia.

As *professional competencies* data and AI knowledge, practical competencies and interdisciplinary domain know-how were identified. These include the understanding of fundamental concepts of data science and AI as well as the selection, use and evaluation of relevant AI tools. They also focus on designing and programming applications that incorporate AI capabilities, as well as understanding the technical fundamentals and technical and business processes for adapting AI solutions to the application domain. The identified *methodological competencies* focus on process and systems thinking, AI problem solving, and AI reflection. Process and systems thinking emphasizes analyzing systems, identifying optimization opportunities, and improving AI processes, while AI problem solving involves defining problems suitable for AI, evaluating tools and constraints, and solving complex problems using AI. In addition, the AI reflection competency area focuses on assessing the broader implications of AI technologies and personal responsibility in their use. The *social competencies* emphasize interdisciplinary communication and collaboration and include, for example, communicating AI concepts to stakeholders, working in teams, and adapting communication styles. Finally, the *self-competencies* highlight learning and curiosity as well as creativity. The former includes independent learning, curiosity, and information gathering, while creativity encourages challenging existing processes and experimenting with AI solutions.

Overall, the identified competency profile provides a basis for further operationalization in curriculum development or course design, as well as a starting point for the development of domain-specific AI competency assessments for engineering education (highlighted in the state of the art Section 3.2.6). By moving from the generic and broad to a particular discipline, it also illustrates how AI competencies can be conceptualized in the context of a discipline. The domain-specific conceptualization, therefore, anchors AI competencies in a domain context [146, 216, 255]. At the same time, it also provides a starting point for addressing the limitations of a broad scope on AI in engineering and for framing a more detailed role-based conceptualization as discussed in Section 4.4 and in [pub:17].

Chapter 5 provided an example of the operationalization and integration of AI competencies at the program level. Previous studies have identified a gap in scholarship on curriculum development activities in higher education [163] and called for the development of interdisciplinary offerings in the context of AI [31, 57]. This chapter examined the process and outcome of a case study of curriculum development for a novel bachelor's program in AI in engineering. In this context, the chapter proposed a structured participatory development process based on the curriculum workshop approach [102, 331] and backward design [330]. In addition, a formative evaluation of the development outcomes was conducted using curriculum mapping and focus group interviews with educators and industry practitioners.

Conducting an in-depth investigation of a case study of curriculum development in the context of AI and engineering, contributed to a process and outcome perspective of the development of an interdisciplinary AI curriculum. Following previous work on curriculum development processes (cf. Section 2.2), the chapter found that the participatory development method of curriculum workshops supported interdisciplinary curriculum development by fostering collaboration and structured exchange of ideas among participants from different disciplines. In particular, factors such as flexibility (the ability to respond to participants' needs) and transparency (participants' knowledge of the current state and tasks) contributed to engagement in the development process. In addition, participation in program development supported ownership and the perceived quality of the program. Given that faculty have strong perceptions of their own disciplines and how these shape their curricular decisions [172, 292], these findings highlight the importance of stakeholder engagement in interdisciplinary curriculum development. However, to address the limitations of the scope of one case, more curriculum research is needed to examine various process aspects of interdisciplinary curriculum development with a focus on AI and across institutions.

In examining the outcomes of the curriculum development, the chapter found that educators perceive interdisciplinarity as a strength, but find it difficult to implement at the curricular level. This is consistent with previous studies that highlight the challenge of developing a coherent interdisciplinary curriculum and pedagogical approaches [152, 312], or integrating transversal competences while managing student workload [178]. For example, the qualitative interview study on developmental outcomes highlighted that achieving interdisciplinarity in the curriculum requires more design considerations and scaffolding to integrate content across courses. This finding is supported by the learning theory of constructivism [91, 293], which emphasizes the importance of learners actively constructing knowledge by connecting new information to their existing understanding. The finding also emphasizes the responsibility of educators in scaffolding interdisciplinarity [197]. Thus, at the program level, it requires additional horizontal (same semester) and vertical (across semesters) communication among educators teaching in the program to ensure coherence and integration. It also implies that interdisciplinary programs require more communication with students to scaffold the links between modules and the overall competency profile. These findings add a practical and interdisciplinary perspective to previous research along the lines of integrated curriculum design [9]. Overall, from an outcome perspective, the developed AI and engineering curriculum is expected to be effective and can be used as a practical reference for educators and curriculum developers, providing a model for an AI and engineering program that can be adapted in different contexts.

Chapter 6 focused on empowering educators who are at the core of implementing competencies, and changing curricula and courses [172]. Previous research has highlighted that educators face the challenge of *adapting their teaching process*, for example integrating AI into their routine and learning activities or changing their assessment forms, as well as reflecting on *curricular changes* to prepare their students for the future workplace (cf. Section 3.4). Although it has been recognized as a challenge and a recommendation [31, 129], to date there has been no systematic effort to change the content of subjects and work on curriculum development on course and program level. In addition, structural support for educators in higher education in terms of curricular change has been limited [138, 172].

To address this gap, Chapter 6 contributed a practical artifact of the AI Course Design Planning Framework as a structural guide to support educators in developing and integrating AI competencies into courses. Specifically, it used a design-based research approach to work with educators in the field to support them in reflecting on curricular changes and integrating AI competencies. The chapter described three design-based research cycles to develop and evaluate the AI Course Design Planning Framework (Figure 6.3) as a visual guide and reflection tool.

With a focus on supporting educators, this chapter contributed a novel perspective on educators planning curriculum change and provided a foundation for structuring research efforts in domain-specific AI education across domains. However, the limitations of the work highlighted that the intervention can be further improved for different target groups. In addition, to enhance the support of the intervention, further research could explore providing automated support and recommendations through LLMs and linking to domain-specific conceptualizations of AI competencies. In addition, the development of an online repository of course examples could provide further support and a basis for further research on implementations of AI education.

7.2 Contributions and Implications for Practice

The field of education about AI is just being established, especially in the domain context of engineering education. Therefore, this dissertation contributes broadly in four main areas:

1. **Overview on state of the art in education about AI**: Previous research has focused primarily on the impact of AI in education [31, 66], neglecting education about AI. Chapter 3 took a novel attempt to contextualize curricular changes

related to AI at a systems level, as well as to structure the field of AI competencies and their respective operationalizations in curricula and courses, with a focus on the application context of engineering education. It also provided a novel perspective on the challenges for educators in adapting curricula and methodologies.

2. **Conceptualization of domain-specific AI competencies for engineering**: To address the conceptualization challenge, Chapter 4 provided the first domain-specific conceptualization of AI competencies for engineering education, following the calls for a bottom-up approach to competencies [8] and anchoring AI competencies in the disciplines [146, 153, 255].
3. **Conceptualization and validation of the program development and outcome of an interdisciplinary program for AI in engineering**: Chapter 5 contributed a novel development process and outcome for an interdisciplinary AI curriculum, highlighting the complexities of development and implementation. This addresses the challenge of operationalization with a need for scholarship on curriculum development activities [163] and a call for the development of interdisciplinary offerings [31, 57].
4. **Structural framework for educators in integrating AI competencies into courses**: Addressing the challenge of empowering educators, Chapter 6 contributed a practical structural guide for educators to integrate AI competencies into their domains. In addition to its practical value, this provides insights into the conceptualization of domain-specific AI courses and a foundation for further research efforts to provide educators with educational and support tools.

Overall, the contributions highlight the interdisciplinary nature of this work, which contributes to engineering education, AI education, and broader curriculum science.

Integrating the Levels Reiterating the systems perspective visualized in Figure 7.1, the dissertation contributed on a supra-level with the conceptualization of competencies that influence the meso-level of institutions in designing their programs as well as the micro-level of educators in making curricular choices in their courses. Thus, although their influence is at different levels, these three contributions are interrelated. For example, from a micro perspective, educators face the challenge of staying informed about changing competencies, curricular requirements at the institutional level, and other influences, while also having influence at the institutional level. The figure also provides a basis for highlighting implications for practice and recommendations for different stakeholders.

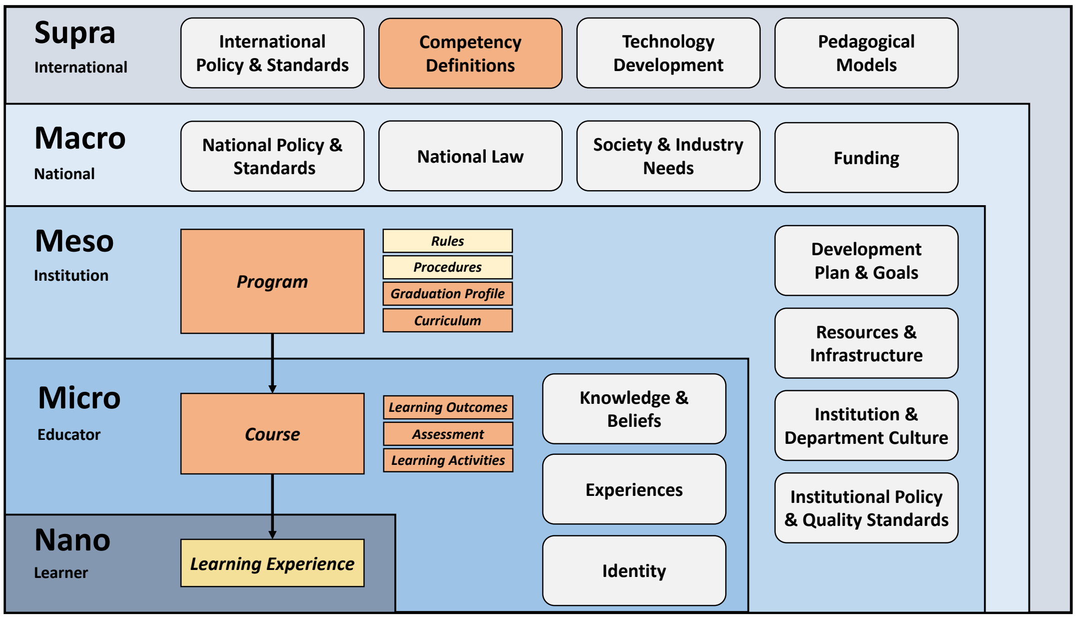

Figure 7.1: Revisiting system model of influences on programs, courses, and learning experiences on different levels. The light-gray boxes demonstrate influence factors along the levels while the orange boxes highlight the main areas addressed in the dissertation.

Implication for Practice Through its applied nature, the dissertation has multiple implications for practice:

1. **Domain-specific AI competencies for engineering education**: Addressing the difficulty for policymakers and educators in conceptualizing AI competencies, Chapter 4 proposed a domain-specific conceptualization of AI competencies targeting the application domain of engineering. This can serve as the basis for a more specific role-based conceptualization in sub-disciplines, or for an overarching catalog of AI-related learning objectives in engineering.
2. **Process for interdisciplinary curriculum development**: To address the challenge of developing interdisciplinary AI programs, Chapter 5 contributed a process and materials to replicate the process in other curriculum development contexts.
3. **Structural guide for integrating AI competencies for educators**: Addressing the challenge of integrating AI competencies at the domain-specific course

level, Chapter 4 contributed a practical framework that can be used by educators to structure and reflect on these topics. It can also be used as a resource for curriculum developers and serve as a starting point for sharing and collecting insights on domain-specific AI education across higher education institutions.

7.3 Recommendations

From the contributions and findings of this dissertation, we can draw several recommendations for policymakers (supra and macro level), educational leadership (meso level) and educators (micro level) that can support the integration of AI competencies in engineering education and beyond:

Policymakers

1. **Develop and establish AI competency frameworks and align accreditation standards**: Build consensus at the national and international level on different conceptualizations of AI competencies, especially involving different scientific communities to develop domain-specific conceptualizations of AI competencies.
2. **Promote interdisciplinary curricular initiatives**: Enable and encourage educational institutions to use innovative curriculum development methods, such as curriculum workshops, to foster collaboration among educators from different fields. This requires funding, facilitation, and appropriate freedom for higher education institutions to take risks and experiment, and funding for scholarship on curriculum change initiatives.
3. **Adapt quality and management tools**: Develop more responsive and dynamic quality assurance and management tools for higher education that promote flexibility and take interdisciplinarity into account.

Educational Leadership

1. **Promote flexibility and transparency in curriculum development**: Implement institutional policies that ensure flexible processes and clear communication of expectations and roles that effectively involve all stakeholders in curriculum design. Provide support structures for curriculum development and improvement.
2. **Advance effective communication among educators**: Support vertical and horizontal communication strategies that enhance coherence in (interdisciplinary)

programs and ensure alignment, integration, and transfer of educational content across modules.

3. **Stimulate and promote the training of educators and students in AI**: Prepare educators for the challenge of curricular and methodological change, with a particular focus on domain-specific applications of AI next to the general use of AI in teaching.

Educators

1. **Reflect on integrating AI competencies into courses**: Use tools such as the AI Course Design Planning Framework or a role-based approach to reflect on relevant AI competencies and related learning objectives for the domain courses.
2. **Leverage and contribute to OERs**: Use OERs to fill expertise gaps or provide diverse learning materials, and contribute back by sharing examples or own materials.
3. **Learn, experiment and share**: Learn and experiment with new forms of AI education or the use of AI in education, and collaborate with other educators on the learning journey.

7.4 Directions for Future Research

The discussions in the main chapters highlighted limitations of scope and methodological approaches, as well as future research directions in the different contexts (see Section 4.4, Section 5.5, Section 6.5). The following aspects highlight some broader research directions to build on this work and further explore AI education and engineering education research and practice:

Mapping Use of AI in Engineering Practices and Education Following the call of Almatrafi, Johri, and Lee [8], there is a need for a more bottom-up understanding of competencies. The empirical work of the thesis included expertise and perspective from industry both in the development of a competency framework (Chapter 4) and in the evaluation of the outcomes of curriculum development (Chapter 5). However, competencies are developed in specific contexts, serve tasks, and are associated with roles. In addition, engineering practices are changing rapidly in response to the advanced capabilities of AI models. For example, programming support with LLMs is becoming more normalized. Thus, from a research and practice perspective, there is a need to further understand how different AI algorithms and tools are used in engineering practices (see [pub:5] as an example). Moreover, these changes need to be reflected in curricular changes in engineering education, for example, when to allow or disallow the use of AI tools in learning programming.

Enhancing System Perspective of Integrating AI Competencies in Domains The dissertation highlighted how domain-specific AI competencies can be conceptualized and operationalized at the program and course level. The results show that curricular changes for AI education need to take place in the context of application disciplines, leading to a new dynamic in higher education institutions. Figure 7.1 demonstrated the multiple influences on these changes. However, investigating the impact of these characteristics was beyond the scope of this work. Therefore, further research is needed to examine the impact of different influences on curriculum change initiatives, potentially building on social and organizational theories [279]. Further research could, for example, follow the idea of analyzing the organizational characteristics of AI programs, building on previous research on interdisciplinary programs [152]. Alternatively, it could look at different levels, for example comparing institutional characteristics and curricular implementation, or conducting further studies on the influence of faculty training on the AI adoption in higher education. It could also include further benchmarking by collecting evidence on program outcomes and student learning in interdisciplinary AI programs.

Moving towards Curriculum Flexibility and Autonomy AI demonstrates the dynamics of a technology that is influencing practices in multiple fields. Previous research has shown that higher education institutions, due to their structure and conservatism, have not been very successful in dealing with curricular change [138]. Beyond the scope of this work, there is a need to develop new approaches to curricular flexibility and autonomy and, more broadly, to corresponding system changes in the context of quality management, policies and incentive structures in higher education institutions [242].

Concluding Remarks: AI as Amplifier

The intensified discourse on AI and education in recent years [31, 66] demonstrates how AI can act as an amplifier for the education system [229]. In view of this amplifying effect, the question of what the education system is aiming at becomes more relevant. An exemplary target variable of higher education is professional success (cf. [251]). A focus on this goal has an impact on the competency goals, as they should, for example, enable future-proof employability. Accordingly, assessment formats should be more closely aligned with professional contexts and teaching methods could be more project-based. If this target variable is not explicitly discussed, but implicitly assumed, AI reinforces these developments to align education with regard to labor market-oriented usability and self-optimization [140, 146].

Some of the key challenges in integrating education about AI and AI in education include curriculum development, infrastructure, lack of ethical considerations, and educators' knowledge [31]. In addition, there are overarching ethical, political, social, and legal issues beyond the scope of this work [183]: What does fairness look like in these systems? How can AI systems contribute to educational equity or exacerbate inequality? How can a legal framework be created around this new reality? What are the dangers of ignoring the issue? How strong should commercial partners be included in education? What rights do learners have over their data and products? Should we rely entirely on open models for the social mission of education? Can AI as a technology be the reason or the lever to think about new learning cultures?

In collaborations and workshops, we touched upon multiple of these questions, e.g., on privacy-preserving ML [pub:15], developing trustworthy models for educational data [pub:3], and discussing ethical, legal and social implications [pub:13, pub:14, pub:21]. The debates also show that many questions remain unanswered.

This can be addressed on two levels: On the one hand, more space should be created for experimentation and critical reflection at universities, and the results should be fed back into the community in an iterative way. Given the speed of development, low-threshold, collaborative development and design between students, faculty, and other stakeholders is essential [188]. However, access to AI models, infrastructure and training should also be created as a prerequisite and framework for this [pub:21]. On the other hand, research is also needed, especially on learning effectiveness, the design of new learning scenarios and critical monitoring [31]. This should be done with a stronger theoretical focus than before [343]. In conclusion, AI should not be seen as a deterministic factor that can influence education. Instead, it is important to examine and test the new possibilities offered by (generative) AI at all levels of research and practice in a reflective and critical, but also open and experimental manner.

A Questionnaires

A.1 Interdisciplinary Competency Profile Questionnaire

The interview guide for the semi-structured interviews with industry and research experts working at the intersection of AI and engineering. Before the interview, a short introduction was given and contextual information about the interviewee such as the company size, industry, position was noted. Moreover, an introduction to the work was given and consent for recording obtained.

Can you briefly tell us what your company does and what role you play in the company?

Level and Potential

- Do you already use artificial intelligence in processes or products or plan to do this?
- Where do you see opportunities and where challenges?
- Do you use more external software or in-house solutions?

Processes/Activities in Development (If no systems have been developed yet, ask how they would proceed.)

- Can you briefly explain the steps you usually go through from idea to deployment?
- How are these systems maintained?
- Who is responsible for this area (AI implementations) in the company?
- How are potential areas of application or use cases identified? Who is responsible for this?

Competencies

- Do you already have a team that deals with intelligent solutions?
- From which disciplines/study programs/competencies is this team composed?

If you had to hire a person:

- Which professional competencies are particularly important in the field of artificial intelligence?
- What specific skills must a person have?
- In your experience: What competencies are lacking in graduates?

Here, especially pay attention to depth: What would you consider most important?

Summary and Reflection

- Summarize main points from the interview: Is there anything else you would like to add?

A.2 Competencies Content Validity Survey

Introduction

Dear Participant,

Thank you for contributing your expertise towards creating an improved understanding of AI competencies for engineers. Note that in the context of this survey, the term AI is used broadly and encompasses multiple approaches including Machine Learning, Deep Learning, Symbolic AI, and Generative AI.

If you choose to participate in this research, you will be asked to rate the relevance and clarity of a set of competency items and then have the opportunity to provide feedback for future revisions and improvements. The estimated time for completion of the survey is approximately 6-15 minutes.

Your responses will be kept confidential and analyzed for research purposes based on the information stated in the privacy policy below.

By proceeding with the survey below (clicking "Next"), you indicate that you have read and understood the privacy policy and consent to participating in the study as described in the privacy policy. If you do not wish to participate, please close the browser window to exit the survey.

Competencies Part

Please rate each competency item for its relevance and clarity according to the following scales.

Relevance: How relevant is this competency for engineers working with AI?
Scale: *1: not relevant, 2: somewhat relevant, 3: quite relevant, 4: highly relevant*

Clarity: Is the wording of this item clear and understandable?
Scale: *1: not clear, 2: item needs some revision, 3: clear but needs minor revision, 4: very clear*

Data and AI Knowledge

Competency Item	Relevance	Clarity
Understand fundamental concepts of AI		
Select and utilize appropriate AI tools for different use cases		
Build and evaluate AI models		
Additional comments or suggestions for this competency cluster:		

Practical Competencies

Competency Item	Relevance	Clarity
Design and program applications with AI functionalities using relevant languages and frameworks		
Work with various AI frameworks and platforms		
Integrate AI components into existing IT infrastructure		
Additional comments or suggestions for this competency cluster:		

Interdisciplinary Domain Know-How

Competency Item	**Relevance**	**Clarity**
Understand the technical foundations of the application domain		
Understand business processes in the application domain		
Implement domain-specific AI solutions		
Additional comments or suggestions for this competency cluster:		

Process- and Systems Thinking

Competency Item	**Relevance**	**Clarity**
Structure, analyze and break down systems and processes		
Identify data-driven optimization opportunities		
Analyze and improve AI-enhanced processes		
Additional comments or suggestions for this competency cluster:		

(AI) Problem Solving

Competency Item	**Relevance**	**Clarity**
Identify and define real-world problems suitable for AI solutions		
Assess available tools, data, and constraints for AI problem-solving		
Develop and implement AI strategies to address complex issues		
Additional comments or suggestions for this competency cluster:		

AI Reflection

Competency Item	**Relevance**	**Clarity**
Assess the social, legal, environmental and ethical implications of AI technologies		
Assess usefulness of AI in an application context		
Reflect on personal responsibility and professional ethics in AI		
Additional comments or suggestions for this competency cluster:		

Interdisciplinary Communication and Cooperation

Competency Item	**Relevance**	**Clarity**
Communicate AI concepts and behavior to diverse stakeholders		
Collaborate in multi-disciplinary project teams		
Adapt communication style to different stakeholders		
Additional comments or suggestions for this competency cluster:		

Change Management

Competency Item	Relevance	Clarity
Manage and shape change processes considering organizational dynamics		
Address concerns and resistance to AI adoption		
Inspire change by communicating AI value and potential		
Additional comments or suggestions for this competency cluster:		

Leadership and Decision Making

Competency Item	Relevance	Clarity
Organize and coordinate diverse AI project teams effectively		
Make strategic decisions regarding AI implementation		
Align AI initiatives with organizational goals		
Additional comments or suggestions for this competency cluster:		

Learning and Curiosity

Competency Item	Relevance	Clarity
Acquire and apply new AI knowledge independently		
Curiosity and openness to learn new topics		
Research and gather information from various sources		
Additional comments or suggestions for this competency cluster:		

Creativity

Competency Item	Relevance	Clarity
Questioning the status quo of existing processes		
Re-imagine processes and systems with AI integration		
Experiment systematically with AI-based solutions		
Additional comments or suggestions for this competency cluster:		

Demographics and Statistics

Please indicate your levels of experience and demographics data to allow us better analyze the data.

AI Expertise and Experience How do you rate your own AI expertise and experience?

- No AI knowledge/experience at all
- Basic idea of what AI is
- Good understanding of how AI works, where it is used, etc.
- Deep understanding of AI (conducted initial AI research/development/knowledge accumulation)
- Very deep understanding of AI (several years of intensive AI research/development/knowledge accumulation)

Frequency of Engagement with AI How would you rate your frequency of engagement with AI?

- Almost never
- Less than once a week

- Approximately once a week
- Almost every (working) day
- Every day

Engagement Duration Since when do you engage with AI?

- 0 to 1 years
- 1 to 3 years
- 3 to 10 years
- More than 10 years

Demographics

- **Age:** 18 - 29 years | 30 - 39 years | 40 - 49 years | 50 - 65 years | 66 and more
- **Highest Level of Education:** Secondary school leaving certificate | High school diploma | Bachelor's degree | Master's degree | Doctorate/PhD | Professorship | Other
- **Gender:** Female | Male | Other/Not specified
- **Current Role:** Student | Employed at research or educational institution | Employed at a company | Self-employed | Other
- **Main Engineering Domain:** Aerospace | Biomedical | Chemical | Civil | Computer/Software | Electrical | Environmental | Industrial | Materials | Mechanical | Nuclear | Petroleum | Other

Closing Thank you for providing your expertise in this matter.

A.3 Curriculum Development Process: Evaluation Survey

This is the translated version of the questionnaire of the evaluation on the curriculum workshop method (described in Section 5.2.5) as of 04.11.2023. The original questions were posed in German.

Introduction

Last year, between January and July, we conducted a total of ten curriculum workshops (CWs) as online workshops to collaboratively develop the curriculum for the AI Engineering degree program. A key outcome of these CWs was the module matrix, based on which the module catalog could be created. Along the way, a profile of the degree program was developed, content clusters were created, learning outcomes were established, and based on that, the competency profile was created. From an organizational perspective, a particular challenge in these CWs was the interdisciplinary orientation of the degree program and the joint development despite different locations.

We would like to take a final look at the curriculum workshops with a bit of distance and provide you with the opportunity to evaluate them. For a better overview, we have compiled the various CWs below. Participation in the survey takes about 5-10 minutes. All information will be treated confidentially and anonymized, in compliance with data protection regulations, and evaluated scientifically. Thank you very much for your participation.

Participation in the Curriculum Workshops

How many curriculum workshops did you approximately participate in? Please refer to the period from January to July 2022.

- I did not participate in any of the CWs.
- 1-2
- 3-6
- 7-10

The following will address an evaluation of the curriculum workshops in general as well as your opinion on the method of the curriculum workshop. Finally, we would like to ask you a few questions about yourself. For further completion of the questionnaire, participation in at least one curriculum workshop is a prerequisite!

Final Evaluation of the CWs

How do you assess the following aspects of the implementation of the curriculum workshops? Try to find an average based on the workshops you participated in. Please respond on a scale from 1 "strongly disagree" to 5 "strongly agree".

1. The curriculum workshops were well prepared.
2. The tasks were clearly formulated and understandable.
3. The work in small groups was helpful for the idea generation process.
4. The duration of the workshops was appropriate.
5. The pace of the process was appropriate.
6. The curriculum workshops were well followed up.
7. The interests of individual participants were adequately considered.

8. The use of collaborative work tools (e.g., Miro, Excel) was helpful for the online implementation of the curriculum workshops.

Please evaluate the following statements regarding the method “curriculum workshop” on a scale from 1 “strongly disagree” to 5 “strongly agree”.

The method of the curriculum workshop...

1. ...was helpful in exchanging ideas and concepts.
2. ...was helpful in making joint decisions.
3. ...was helpful in developing formulations.
4. ...was helpful in creating the competency profile.
5. ...was helpful in developing the module matrix.
6. ...was helpful in getting to know each other.
7. ...is a suitable tool to consider interdisciplinary perspectives.
8. ...is a participatory method.

Please evaluate the following statements regarding interdisciplinarity in the curriculum workshops on a scale from 1 “strongly disagree” to 5 “strongly agree”.

1. I was able to collaborate fruitfully with representatives from other disciplines and/or other academic cultures.
2. I consider interdisciplinary collaboration to be beneficial overall.
3. Communication difficulties between disciplines and/or academic cultures were adequately addressed by moderation.

In your opinion, were there problems with interdisciplinary collaboration? Please provide an assessment and also indicate the frequency. Scale from “no”, “yes, occasionally“ ”yes, often“, and ”yes, always“.

There were problems with interdisciplinary collaboration because of ...

- ...a different understanding of central concepts because of various culturally defined definitions.
- ...differing interests in the development of the degree program.
- ...varying levels of engagement among participants from different disciplines.

Weaknesses and Strengths of the Curriculum Workshop

What do you see as the weaknesses of the curriculum workshop as a method for interdisciplinary curriculum development? *[Open Question]*

What do you see as the strengths of the curriculum workshop as a method for interdisciplinary curriculum development? *[Open Question]*

In your opinion, would the use of the curriculum workshop method be advisable in the future creation of an interdisciplinary degree program?

- Yes, definitely.
- Yes, probably.
- No, probably not.
- No, definitely not.
- Don’t know.

Demographics

Which academic background do you primarily identify with? Multiple selections are possible.

- Computer Science
- Engineering Domain
- Other academic background, namely: ________________________________

Which of the following personnel categories do you identify with?

- Professor
- Research Associate
- Student
- Other personnel category, namely: ________________________________

Thank you for your participation!

Do you have any further comments about the curriculum workshops or the survey in general?

A.4 Curriculum Development Outcome: Questionnaire for Focus Group Interviews

This describes the translated questionnaire used as interview guide in the focus group interviews, described in Section 5.2.6. The interviews were conducted from 26.01.2024 till 26.02.2024. The original questions were posed in German.

Introduction

The introduction followed a standard procedure. First, the moderators introduced themselves and presented the agenda and objectives with a emphasis on the evaluation of the design of the program not the implementation. Next, focus groups as a method was introduced and participants introduced themselves with name and professional background. Last, the tools were introduced and final consent for recording obtained.

Participant Backgrounds via Online Tool

1.1 Teaching experience: How long have you been teaching?

1.2 Curriculum development experience: Have you ever contributed to developing a curriculum?

1.3 Attitude towards interdisciplinary programs: What is your attitude towards interdisciplinary programs in general?

Topic: Representation of the Competency Profile through the Curriculum

We would like to give you five minutes to review the competency profile (which we have already sent to you in advance). Afterwards, we will present the module matrix and would like to answer the following question (see 2.1).

2.1 Is the competency profile achieved with this curricular arrangement of modules? (Number and justification). (Scale: *1 - very good* to *5 - not good at all*)

Discussion: Justification of the evaluation, inquiries, and deepening in the insights and reasoning

Topic: Content, Expectations, and Acceptance

From a content and disciplinary perspective:

3.1 How well does the curriculum meet the professional requirements of your discipline / your area of expertise (e.g., computer science, mechanical engineering, etc.)? (Scale 1 Very good to 5 not good at all)

Discussion: Justification of the evaluation, inquiries, and deepening in the insights and reasoning

3.2 Strengths and weaknesses: Where do you see strengths and weaknesses in the curriculum?

3.3 Structure: How do you assess the structure of the program in the proposed course sequence? Do the subjects build meaningfully on each other?

3.4 Expectations: What expectations do you have of an AI Engineer?

Topic: Interdisciplinarity

4.1 Interdisciplinarity: In relation to the program: Where do you see opportunities and risks in interdisciplinarity?

Optional Additional Questions

O.1 Studyability: How appropriate do you find the content and workload for the target audience?

O.2 Changes: What changes would you recommend for the curriculum to better prepare students for the challenges and opportunities that may arise in the future?

O.3 Balance: How do you assess the balance between foundational knowledge and specialization?

Conclusion and Thanks

Are there any further comments from your side? Thank you and next steps: Brief questionnaire – also for additional ideas that may arise

B Further Details and Results

B.1 Further Publications

In addition to Table 1.2, the following articles have been published but are not directly included in the dissertation:

Johri, A., **Schleiss, J.** & Ranade, N. (2025). Lessons for GenAI Literacy from a Field Study of Human-GenAI Augmentation in the Workplace. *2025 IEEE Global Engineering Education Conference (EDUCON 2025).* [pub:5]

Stracke, C. M., Griffiths, D., Pappa, D., Bećirović, S., Polz, E., Perla, L., Di Grassi, A., Massaro, S., Skenduli, M. P., Burgos, D., Punzo, V., Amram, D., Ziouvelou, X., Katsamori, D., Gabriel, S., Nahar, N., **Schleiss, J.**, & Hollins, P. (2025). Analysis of Artificial Intelligence Policies for Higher Education in Europe. *International Journal of Interactive Multimedia and Artificial Intelligence 9(2)*, 24-137,. [pub:26]

Johri, A., Hingle, A. & **Schleiss, J.** (2024). Misconceptions, Pragmatism, and Value Tensions: Evaluating Students' Understanding and Perception of Generative AI for Education. *Proceedings of 2024 IEEE Frontiers in Education (FIE) Conference*. [pub:4]

Schleiss, J. & Magdowski, M. (2024). Mastery Learning in der Hochschulbildung: Eine Einordnung von der Theorie zur Praxis. In: *Digitale Prüfungsszenarien in der Hochschule*. [pub:20]

Schleiss, J., & Stober, S. (2023). Trustworthy Academic Risk Prediction with Explainable Boosting Machines. In: *Proceedings of the International Conference on Artificial Intelligence in Education*, 463–475. [pub:3]

Schleiss, J., Bachus, L., & Djabarian, Y. (2023). Co-creating Visions with Higher Education Institutions: A case study in the German Higher Education Landscape. In: *Proceedings of the EDEN 2023 Annual Conference*. [pub:11]

Lang, S., Siegert, I., Artiushenko, V., & **Schleiss, J.** (2023). AI Engineering als interdisziplinäres Einführungsmodul zwischen Künstlicher Intelligenz und Ingenieurwesen. In: *Informatik 2023 - Designing Futures: Zukünfte gestalten (pp. 381–384). Gesellschaft für Informatik e.V.* [pub:7]

van der Werf, V., van Helden, G., **Schleiss, J.**, & Saunders-Smits, G. N. (2023). A Framework For Investigating The Application Of Educational Theories In Engineering Education Research. In: *Proceedings of 51st European Society for Engineering Education (SEFI) Conference*, 1402–1415. [pub:27]

Schleiss, J.; Brockhoff, R.; & Stober, S. (2022). Projektseminar Künstliche Intelligenz in den Neurowissenschaften – interdisziplinäre und anwendungsnahe Lehre umsetzen. In: *Anwendungsorientierte Hochschullehre zu Künstlicher Intelligenz. Berlin: KI-Campus*. [pub:11]

Schleiss, J., Günther, K., & Stober, S. (2022). Protecting Student Data in ML Pipelines: An Overview of Privacy-Preserving ML. In: *Proceedings of the International Conference on Artificial Intelligence in Education*, 532–536. [pub:15]

B.2 Curricular Details of all Specializations

This appendix describes the curricular details of all specialization of the AI engineering program as described in Section 5.2.1 and Section 5.2.4.

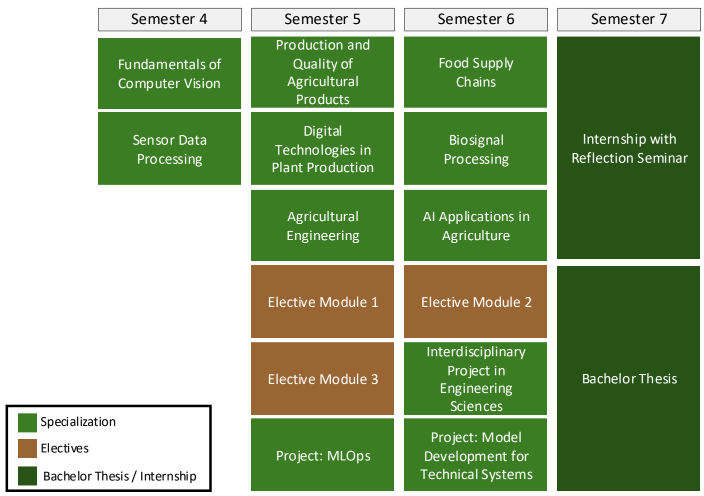

Figure B.1: Curriculum of Specialization *Agricultural Economy and Technology*.

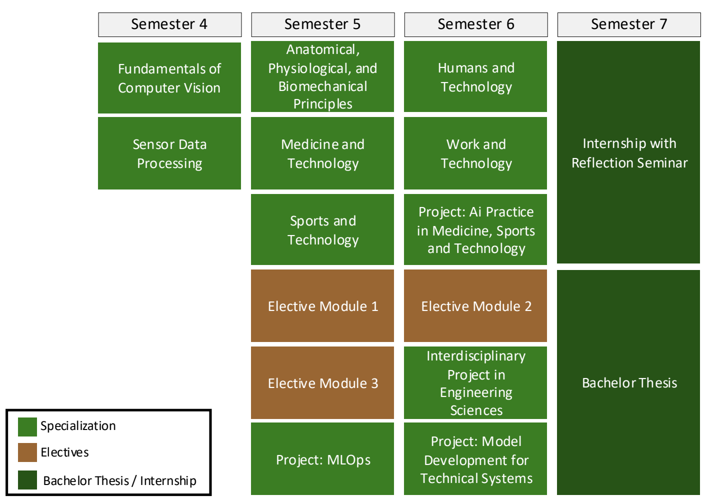

Figure B.2: Curriculum of Specialization *Biomechanics and Smart Health Technologies*.

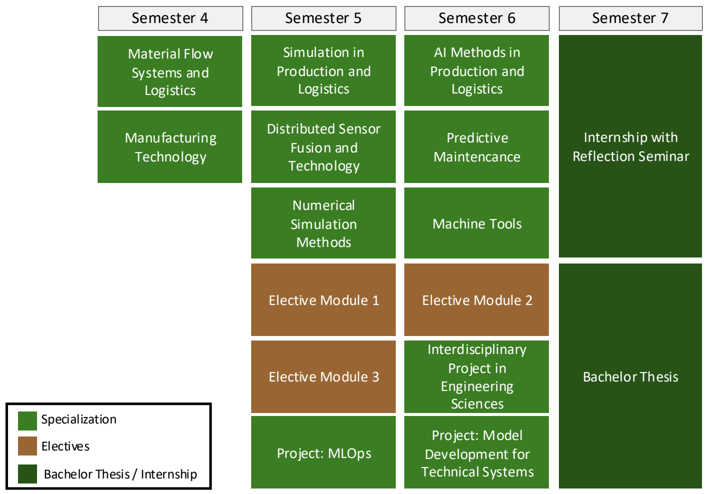

Figure B.3: Curriculum of Specialization *Green Engineering*.

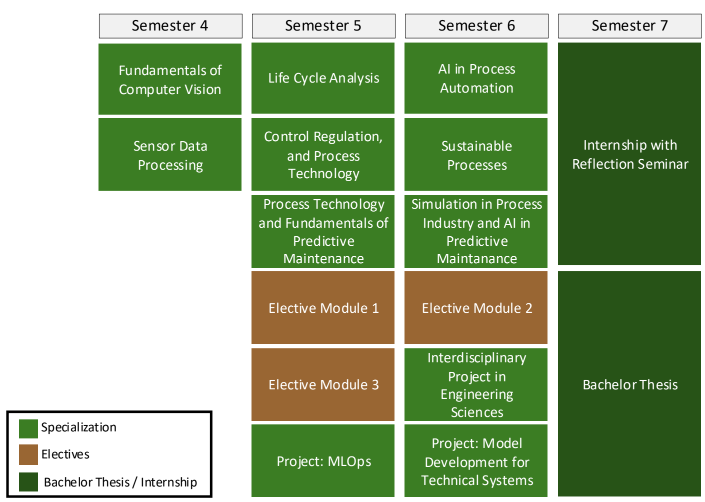

Figure B.4: Curriculum of Specialization *Manufacturing, Production and Logistics*.

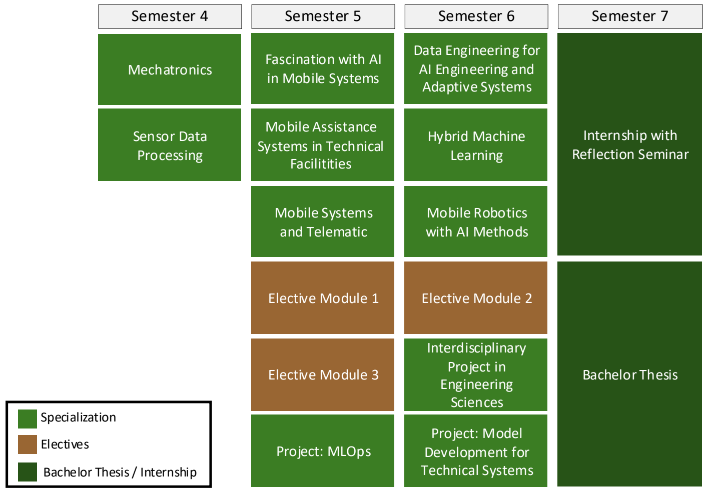

Figure B.5: Curriculum of Specialization *Mobile Systems and Telematics*.

B.3 Curriculum Mapping Details

The following Table B.1 provides the complete curriculum mapping as described in Section 5.2.6 and summarized in Section 5.4. In particular, it maps the competencies described in Table 5.1 to the different modules of the curriculum indicating full ●, partial ◖, and no coverage of subcompetencies.

Table B.1: Curriculum outcome mapping with full, partial, and no coverage of competencies.

ID	Title	Math						Engineering							CS				AI							Spec		P & S			Transdisc			
		Linear Algebra	Statistical Tools	Analysis	Optimization	Machine Learning	Others	Engineering Fundamentals	Physics Fundamentals	Electrical Engineering Fundamentals	Measurement and Sensor Tech	Applied Mechanics	Control Technology	Signal Processing	Object-Oriented Programming	Software Engineering	Software Workflows	Server and Cloud Handling	Data Management	Model Development	Model Visualization	Model Evaluation	Ethics and Technology	Agile Development	AI System Monitoring	Application Area Fundamentals	Process and Data Analysis	Problem Structuring	AI Project Management	Risk Assessment	Cross-Disciplinary Communication	Self-Organization	Project Coordination	Critical Reflection
1	Data Engineering																		●															
2	Introduction to Computer Science for Engineers														●																			
3	Introduction to AI Engineering																					◐	◐					◐	◐					
4	Electrical Engineering Fundamentals									●				◐																				
5	Mathematics 1 for Engineers	●		◐																														
6	Engineering Design Graphics							◐																										
7	Business Administration for Engineers																					◐	◐							◐				
8	Fundamentals of Machine Learning					◐													◐	◐	◐													
9	Measurement technology										●																							
10	Project: Protoytping of AI-Systems																		●	◐	◐	◐			◐			◐	◐		◐	◐	◐	
11	Engineering Mechanics 1							◐	◐			◐																						
12	Deep Learning for Engineers						◐												◐	●	◐	●												
13	Industrial AI Systems							◐																			◐	●			◐			
14	Mathematics 2 for Engineers			●																														
15	Mathematics 3 for Engineers		●	◐																														
16	Project: ML Programming																◐		●	●	●	●		◐				◐	◐	◐	◐	●	●	
17	Software Engineering & IT-PM															●	◐																	
18	Engineering Mechanics 2/3							◐	◐			●																						
19	Explainable and safe AI																				●	◐	◐							◐				
20	AI based Control and Optimization of Technical Systems and Processes				◐			◐					◐							◐														
21	AI Reflection and Ethics																						●							●				◐
22	Signal Processing										◐			●												◐								
23	Sensor Data Processing												●													◐								
24	Introduction to Computer Vision																									◐					◐	◐		
25	Digital technologies in agriculture production																									◐	◐	◐						
26	Production and Quality of Agricultural Products																									◐								
27	Agricultural Technology																									◐	◐							
28	Biosignal Processing																		◐							◐	◐							
29	AI Applications in Agriculture																									◐	◐							
30	Food Supply Chains																									◐								

Continued on next page

Table B.1: *continued from previous page*

ID	Title	Math						Engineering							CS				AI							Spec		P & S			Transdisc			
		Linear Algebra	Statistical Tools	Analysis	Optimization	Machine Learning	Others	Engineering Fundamentals	Physics Fundamentals	Electrical Engineering Fundamentals	Measurement and Sensor Tech	Applied Mechanics	Control Technology	Signal Processing	Object-Oriented Programming	Software Engineering	Software Workflows	Server and Cloud Handling	Data Management	Model Development	Model Visualization	Model Evaluation	Ethics and Technology	Agile Development	AI System Monitoring	Application Area Fundamentals	Process and Data Analysis	Problem Structuring	AI Project Management	Risk Assessment	Cross-Disciplinary Communication	Self-Organization	Project Coordination	Critical Reflection
31	Project MLOps																	●						●	●				◐		●	●	●	
32	Project Model development for technical systems																		●	●	●	●						●	●		●	◐		◐
33	Interdisciplinary Project																		◐	◐	◐	◐		◐		◐	◐	◐	◐	◐	●	◐		◐
23	Sensor Data Processing												●													◐								
24	Introduction to Computer Vision																									◐					◐	◐		
34	Introduction to medical engineering																																	
35	Introduction to sports science and sports engineering																			◐						◐	◐	◐						
36	Work and technology - AI																						◐			◐	◐							
37	Introduction to human anatomy, physiology and biomechanics																									◐								
38	Humans and technology																						◐											◐
39	Project: The practical application of AI in medicine, sports and technology																		◐	◐						◐	◐	◐	◐					
31	Project MLOps																	●						●	●				◐		●	●	●	
32	Project Model development for technical systems																		●	●	●	●						●	●		●	◐		◐
33	Interdisciplinary Project																		◐	◐	◐	◐		◐		◐	◐	◐	◐	◐	●	◐		◐
40	Manufacturing Processes 1											●														◐								
41	Material Handling Systems and Logistics							◐																		◐								
42	Numerical methods for simulation			◐	◐																					◐								
43	Simulation in Production and Logistik																									◐								
44	Introduction to Distributed Sensor Data Fusion		◐								●			◐												◐								
45	AI methods in production planning and control							◐												◐	◐	◐				◐	◐	◐						
46	Predictive Maintenance							◐												◐	◐					◐	◐	◐						
47	Machine Tools							◐				◐														◐								
31	Project MLOps																	●						●	●				◐		●	●	●	
32	Project Model development for technical systems																		●	●	●	●						●	●		●	◐		◐

Continued on next page

Table B.1: *continued from previous page*

ID	Title	Math						Engineering							CS				AI							Spec		P & S			Transdisc			
		Linear Algebra	Statistical Tools	Analysis	Optimization	Machine Learning	Others	Engineering Fundamentals	Physics Fundamentals	Electrical Engineering Fundamentals	Measurement and Sensor Tech	Applied Mechanics	Control Technology	Signal Processing	Object-Oriented Programming	Software Engineering	Software Workflows	Server and Cloud Handling	Data Management	Model Development	Model Visualization	Model Evaluation	Ethics and Technology	Agile Development	AI System Monitoring	Application Area Fundamentals	Process and Data Analysis	Problem Structuring	AI Project Management	Risk Assessment	Cross-Disciplinary Communication	Self-Organization	Project Coordination	Critical Reflection
33	Interdisciplinary Project																		◐	◐	◐	◐		◐		◐	◐	◐	◐	◐	●	◐		◐
23	Sensor Data Processing												●													◐								
24	Introduction to Computer Vision																									◐					◐	◐		
48	Life cycle analysis																									◐					◐			
49	Process technology and fundamentals of predictive maintenance																									◐	◐							
50	Control-, regulation- and process control engineering																																	
51	AI in Process Automation																			◐	◐					◐	◐							
52	Sustainable processes																									◐								
53	Simulation in the Process Industry and AI in Predictive Maintenance				◐																					◐	◐							
31	Project MLOps																	●						●	●				◐		●	●	●	
32	Project Model development for technical systems																		●	●	●	●						●	●		●	◐		◐
33	Interdisciplinary Project																		◐	◐	◐	◐		◐		◐	◐	◐	◐	◐	●	◐		◐
54	Mechatronics 1												◐													◐								
55	Sensor Data Processing												●													◐								
56	Fascination AI in mobile systems																									◐	◐							
57	Mobile assistance systems in the operation of technical systems																		◐							◐	◐	◐	◐					
58	Mobile systems & telematics																		◐							◐	◐							
59	Data Engineering and Adaptive Intelligent Systems																		◐							◐								
60	Hybrid machine learning - knowledge and data-based models of technical systems																									◐	◐							
61	Mobile robotics with AI methods																									◐	◐							
31	Project MLOps																	●						●	●				◐		●	●	●	
32	Project Model development for technical systems																		●	●	●	●						●	●		●	◐		◐
33	Interdisciplinary Project																		◐	◐	◐	◐		◐		◐	◐	◐	◐	◐	●	◐		◐

B.4 AI Course Design Planning Framework

B.4.1 Exemplary Filled Examples

Predictive Maintenance in Engineering

Figure B.6 presents a filled example of the AI Course Design Planning Framework for a course in the context of production operations in engineering. It is assumed that the course is for Bachelor students in the Mechanical Engineering domain in their 6th semester.

AI in the Domain First, in identifying potential use cases, we note that machine and tool failures in production operations are associated with high costs, and thus the goal of predictive maintenance is to service a machine before the tool or other components fail. In this way, the time and cost of machine maintenance can be reduced. In this context, AI techniques are used to predict the optimal maintenance time for machines or tools based on certain machine and sensor measurements.

Second, by understanding the data, we can identify that the underlying data is usually time-series data about sensor measurements that describe the current state and condition of the machine or tool over time. Sensor measurements from different sensors can be used as individual data or combined. Examples include vibration, temperature, sound, and pressure measurements.

Third, looking at the implications of using AI, we find that there are no ethical, legal or social implications of predictive maintenance use cases, as there is no direct human involvement. An interesting aspect to discuss is the legal liability of predictive maintenance in service contracts.

Finally, in terms of additional resources, there are several courses that teach AI concepts related to time series and sensor data, some of which can also be integrated into the course as OER.

Learning Environment The learners in this course have a technical background and a good understanding of mathematical concepts. They also have basic programming experience, mostly focused on C++. After completing the course, they should take on the role of applying and implementing AI techniques for predictive maintenance. The course builds on the knowledge of production technologies and their modeling and simulation, as well as measurement theory that students have acquired in previous semesters.

The instructor has a background in mechanical engineering, especially in manufacturing engineering. Through various research projects, she has acquired some AI knowledge and skills in the context of production systems. Several PhD students of the engineering department are available to support the course.

In terms of internal support, the course runs as a project for one semester for 5 credits (equivalent to 150 hours of work). A potential problem is the access to computer resources. Didactic support would be provided by the university. An internal dataset of vibration sensor measurements is available for the course. In addition, vibration sensors are available for further measurements on the machine.

Course Implementation Regarding the learning outcomes, students will learn about different AI techniques, especially machine learning techniques, to predict the optimal maintenance time for machines and tools. In this context, students will learn which data from machines and tools are most suitable for predicting necessary maintenance actions. Students will also learn the hardware and software design and project planning of predictive maintenance systems. In addition, students should apply programming paradigms and create a holistic application and pipeline from sensor measurements to failure prediction.

Assessment will include a presentation of the project results, documentation of the project and code, and teamwork on the project.

Learning activities include a lecture block on AI-based concepts and traditional methods of predictive maintenance, as well as group project work to build pipelines from sensor measurements to predictions of machine and part conditions. Group presentations and discussions are also planned.

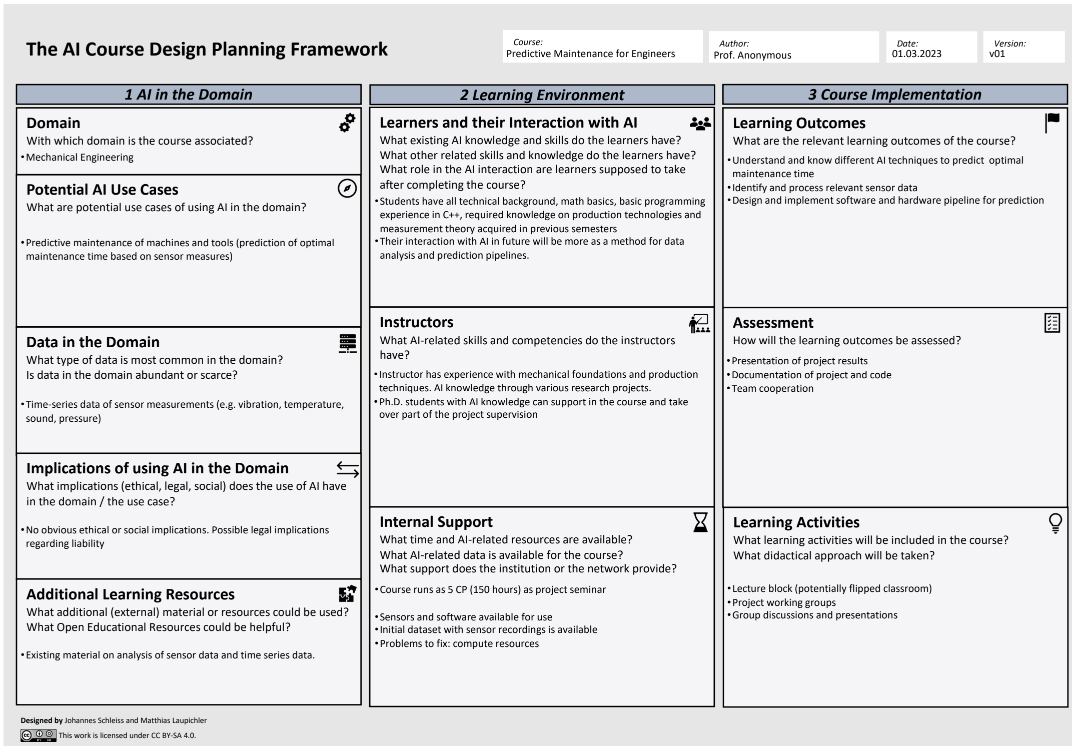

Figure B.6: Exemplar AI Course Design Planning Framework filled for a course of predictive maintenance in engineering.

AI in Radiology

In healthcare, AI applications are being explored in a variety of areas, some of which are already being used in everyday clinical practice. A particularly promising area of application is medical imaging and radiology, where the data consists mainly of relatively standardized image data. Much progress has been made in recent years through research on e.g. Convolutional Neural Networks and Generative Adversarial Networks.

The exemplary course will be created to teach high-semester medical students (i.e., 8th semester or higher) about the application of AI in radiology, its opportunities and limitations, and how AI models work. At this point in their studies, most medical students already have a good understanding of radiology and its core features, as well as a good overview of clinical practice, pathologies, and other domain-specific knowledge.

AI in the Domain While AI is used in many, if not most, areas of radiology, the course focuses on a few selected use cases to demonstrate the potential of AI. It uses a typical radiology use case (i.e., fracture detection), a more neuroradiology use case (i.e., diagnosis of ischemic strokes in the brain), and a use case that uses medical imaging but comes from another discipline, dermatology (i.e., identification of melanoma). The use cases are designed to help students understand the complementary, assistive role of AI programs in today's radiology practice.

Radiologists work mostly with image data. However, the images are not always two-dimensional (e.g., X-ray), but can also be three-dimensional (e.g., Magnetic Resonance Imaging (MRI)). Furthermore, in addition to image data, a variety of other numerical data is often used to train AI models.

The course is designed to teach students that AI is a powerful technology, capable of matching and in some cases surpassing human diagnostic accuracy. However, the goal is not to instill fear of being replaced by machines, but to convey that AI can help meet the ever-increasing demand for high-quality medical imaging. Ethical and legal issues are also discussed, focusing on the need to use only programs that have been certified by the appropriate medical authority. The problem of accountability is introduced as another major implication.

In the field of radiology, image data from real (anonymized) patients can be used to show students the connection to reality. Furthermore, a web-based DICOM viewer can be used to present and compare image data. Jupyter notebooks are hosted on cloud services to give students the opportunity to try programming themselves. Finally, students will have access to basic AI courses to build their AI skills before taking the course.

Learning Environment Since all of the participants in the course will be medical students, all of them will take on the role of either "co-workers and users of AI products" or "collaborators and implementers of AI", and none of the students are expected to have any significant experience with AI. However, some students may have a good understanding and interest in physics, as radiology is a physics-heavy field. In addition, data preparation techniques will be easily understood by most students, since segmentation and classification are part of their regular studies.

As for the faculty, the course is taught by an interdisciplinary group of faculty consisting of clinical radiologists and AI researchers who work at the intersection of AI and radiology but have a technical, non-medical background (e.g., physicists, or computer scientists). By combining the knowledge and experience of these two fields, we will follow a "best-of-both-worlds" approach in which both groups of experts can contribute their respective strengths without being equally confident in each area.

The 4-week full-time course will be prepared by a Ph.D. student (AI researcher) and an intern (physician) approximately three months prior to the start of the course. They will be supported by a student assistant, and hardware and software will be funded by an internal grant. In addition, two leading researchers in the field have agreed to give guest lectures to demonstrate how AI will change radiology.

Course Implementation The key learning outcomes focus on three main things: 1) understanding AI in radiology and the corresponding use cases, 2) being able to use AI and collaborate with AI programs in clinical practice, and 3) understanding the code underlying AI programs and being able to critically evaluate results, potential biases, etc.

To assess whether students are achieving these outcomes, three different forms of assessment are used. The first is the standard multiple-choice and open-ended exam designed to test knowledge retention. Second, we have students demonstrate real-world AI skills, such as explaining AI models to patients or using commercial AI programs and interpreting their results. Finally, a programming test is designed to assess whether students understand the concepts behind AI models, such as hyperparameter tuning.

Various learning activities are planned to ensure that all learning outcomes are achieved. In addition to more traditional methods such as classroom teaching, more modern activities such as programming exercises or live demonstrations are intended to address the novel nature of AI.

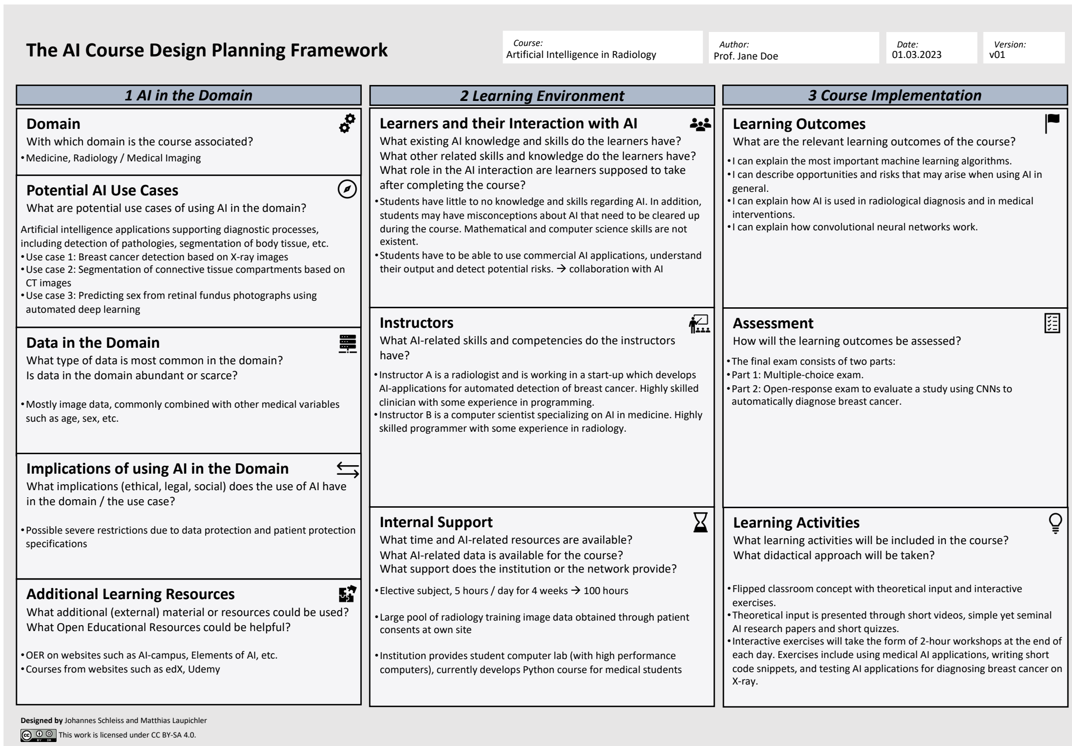

Figure B.7: Exemplar AI Course Design Planning Framework filled for a course of radiology.

B.4.2 Previous Design Versions and Modifications

Figure B.8 demonstrates the previous designed version that was used in the first design cycle. Table B.2 lists the modifications based on suggestions in the first workshop, leading to the presented prototype (Figure 6.3).

Table B.2: List of modifications of the planning framework based on suggestions from expert participants using initial framework (Figure B.8).

Type of Change	Modification
Design and Layout	1. Changing the order of pillars to reflect the order in which they should be filled 2. Numbering the pillars 3. Improving readability through different coloring
Clarity and Usability	1. Renaming the pillars and the categories 2. Adding additional category of domain 3. Improving the clarity of the guiding questions in each category

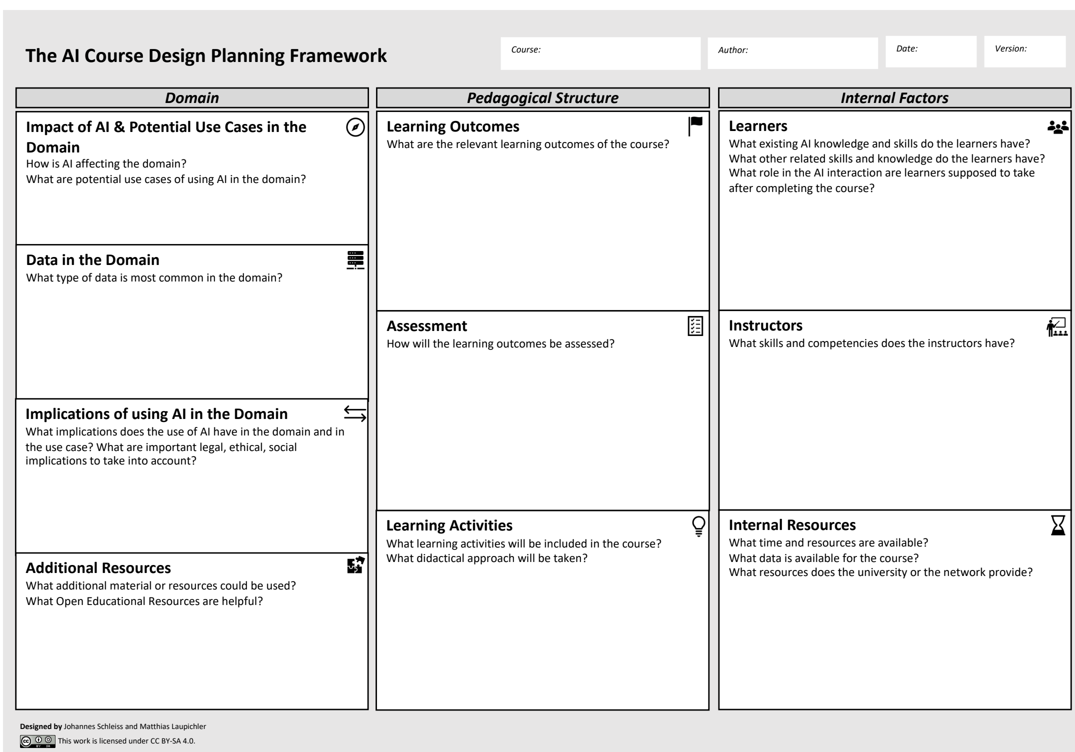

Figure B.8: Version of the framework used in workshop used in cycle 1.

List of Abbreviations

Notation	Description
AAAI	Association for the Advancement of Artificial Intelligence
ABET	Accreditation Board for Engineering and Technology
ACM	Association for Computing Machinery
ADDIE	Analyze, Design, Develop, Implement, and Evaluate
AI	Artificial Intelligence
ATAI	Attitudes towards AI
CDIO	Conceive Design Implement Operate
CS	Computer Science
CSTA	Computer Science Teachers Association
DigComp	Digital Competence Framework for Citizens
EER	Engineering Education Research
EU	European Union
EUR-ACE	European Accredited Engineer
IEEE	Institute of Electrical and Electronics Engineers
LLM	Large Language Model
ML	Machine Learning
MOOC	Massive Open Online Courses
OECD	Organization for Economic Cooperation and Development
OEP	Open Educational Practices
OER	Open Educational Resources
SA	Self-assessment
SAM	Successive Approximation Model
SEFI	European Society for Engineering Education
SOLO	Structure of Observed Learning Outcomes
STEM	Science, Technology, Engineering, and Mathematics
TPACK	Technological Pedagogical Content Knowledge
UNESCO	United Nations Educational, Scientific and Cultural Organization

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Declaration of Use of Generative AI

During the preparation of this work the author used Grammarly and Deepl Write in order to improve the grammar and clarity of the text. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content.

Declaration of Academic Integrity

I hereby certify that I have prepared this thesis without the unauthorized assistance of third parties and without the use of resources other than those indicated; external and my own sources used are identified as such. In particular, I have not used the help of a commercial doctoral advisor. Third parties have neither directly nor indirectly received monetary benefits from me for work related to the content of the submitted dissertation.

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