AIComp

Future skills for a living and working world shaped by AI

Research Report 1: Theory, methodological design, and results of the AI Competence Study 2024

Ulf-Daniel Ehlers, Martin Lindner, Emily Rauch

DHBW
Duale Hochschule
Baden-Württemberg

AI Campus
The Learning Platform
for Artificial Intelligence

NEXT EDUCATION

Imprint

Authors & Team: Ulf-Daniel Ehlers, Martin Lindner, Emily Rauch

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AI-Campus - The learning platform for artificial intelligence: The AI-Campus is the learning platform for artificial intelligence with free and freely accessible online courses, videos, and podcasts to strengthen AI and data skills.

As a research development project, the Federal Ministry of Education and Research (BMBF) and the Dieter Schwarz Foundation funded the AI -Campus, coordinated by the Stifterverband (www.stifterverband.org).
More about the AI-Campus initiative: www.ai-campus.org.
More: www.ai-campus.org

NextEducation: NextEducation is an internationally active research collective at the Baden-Wuerttemberg Cooperative State University. It deals with teaching and research on the transformation of educational organizations and processes, teaching and learning, and lifelong learning processes under the conditions of an increasingly digitalized world. In international and national projects, the research group focuses on the future of educational organizations and learning processes.
More: www.next-education.org

NextSkills: As part of the NextSkills initiative, a German-language competence structure model for Future Skills was developed specifically for the higher education sector in 2019 and 2020. Since then, empirical studies on Future Skills for various educational sectors and specialist domains have been regularly implemented, including AIComp on Future Skills for AI in 2023. The results are made available for open access.
More: www.nextskills.org

Contact: Ulf-Daniel Ehlers, ulf.ehlers@dhbw.de

Preface

In an age of rapid technological developments and social upheaval, we are faced with the challenge of identifying the skills of the future - so-called Future Skills - and understanding how these can be integrated into education and work. These are important to help people actively shape tomorrow's society, to develop technologies further, and above all to use them to strengthen our democracies, to take steps against climate change, and to work towards peace. Against this backdrop, it is a special honor for me to write the foreword for this study, which significantly contributes to the exploration of Future Skills for a living and working world increasingly shaped by artificial intelligence (AI).
This study was conducted by the dedicated research collective NextEducation, which is committed to researching and developing innovative educational models. By conducting this study, we have reached another milestone: the first completely empirical, quantitative construction of a Future Skills model. This model is proof of the research collective's scientific aspirations and the intention to shape future education actively.

I thank all my colleagues who have made this study possible with their expertise, commitment, and passion. Their tireless efforts and vision have significantly contributed to the fact that we can now proudly reflect on such a pioneering project.

I especially want to thank my two co-authors Emily Rauch and Martin Lindner. The study was conducted as part of the KI-Campus project, funded by the Federal Ministry of Education and Research (BMBF) and the Dieter Schwarz Foundation. Our thanks also extend to the many project partners of this project, whose support and cooperation were essential for the success of this study (www.ki-campus.org).
Special thanks are also due to the Baden- Württemberg Cooperative State University (DHBW), its university management, the staff council, and the colleagues and employees who supported and contributed to this project. We would also like to thank the many partners of the DHBW, whose commitment and expertise made a decisive contribution to the success of this study. We would also like to thank the Karlsruhe and Heilbronn Chambers of Industry and Commerce, the Südwestmetall Association, and the many other organizations that supported the study in various ways.

With this study, we are laying the foundations for a deeper understanding of the subject of research, and Future Skills, and offering concrete approaches for their integration into the world of education and work. Our common goal is to set the course for sustainable education and thus make a valuable contribution to society.

Finally, I would also like to thank all the students involved, whose active participation and commitment made this study possible in the first place. Their contribution was an important building block for the success of our joint project.

We have taken an important step toward the future together with this study. I am convinced that the results of this research work will not only provide valuable insights but will also serve as a guide for the development of future-oriented education and labor market strategies

Many thanks to everyone involved for their contribution to this pioneering project.

Ulf-Daniel Ehlers Karlsruhe in March 2024

Due to the amount of data obtained, the specific AIComp competence model will be published in a second part of the report. See www.ai-comp.org

Executive Summary (E)

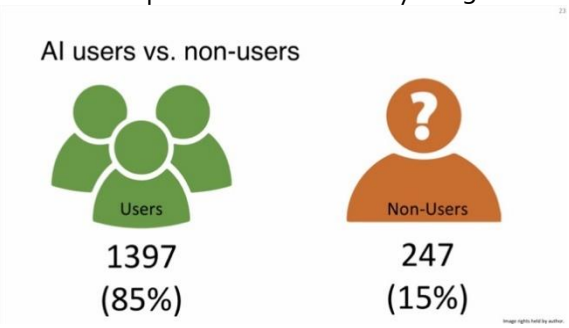
The AIComp study was designed to develop an in-depth understanding of the Future Skills essential for shaping a living and working environment influenced by artificial intelligence (AI). It will be even more heavily determined in the future. The statistical analyses of the major AI study are published in this first research report. A second research report refers to the detailed derivation and construction of the AIComp competence model and is available here: www.ai-comp.org.

As part of the study, more than 1,600 working adults in Germany were surveyed, focusing on the Baden-Wuerttemberg region. The influence of AI on the living and working environments of the respondents was described by them as significant and complex. To do justice to this diversity, a perspective was chosen in the study that looks at the required skills from the point of view of the individuals themselves. This subject-scientific perspective forms the basis for developing the comprehensive model of Future Skills.

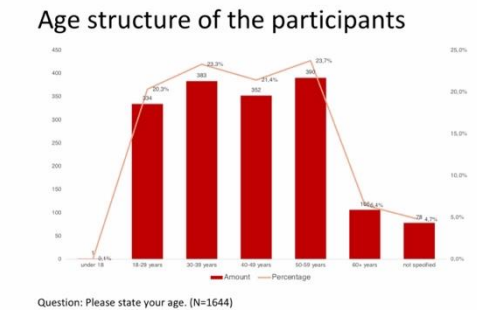
The study presents the basic requirements for assessing these skills and examines the usage behavior of respondents in the context of AI. It offers a comprehensive insight into opinions on AI and sheds light on the range of skills required in the future and those already available, as well as the gap between them. For the study, the Future Skills approach has been extensively theoretically validated. Competence is understood as a disposition and ability to act and is anchored in the theory of action competence theory. The concept of action is rooted in Bourdieu's habitus concept, which describes the habitus as a "generative principle of social forms of practice" and, like competence theory, introduces the concept of disposition (Bourdieu 1997). Borrowings from Bourdieu's capital theory also make it possible to place competence development in a larger context of education as incorporated cultural capital and social practice, e.g. in organizations. The subject perspective is also linked to theoretical works on modern self-socialization theory and the concept of "agency".

An additional aim of the study is to gain insights to formulate strategic guidelines for educational programs to promote AI skills.

Method: The study follows a mixed-methods approach. Based on an analysis of the current state of research, an initial qualitative model for Future Skills was developed and validated through qualitative interviews. The subsequent large standardized quantitative online survey led to 1644 evaluable questionnaires in a two-month field phase in June and July 2023.

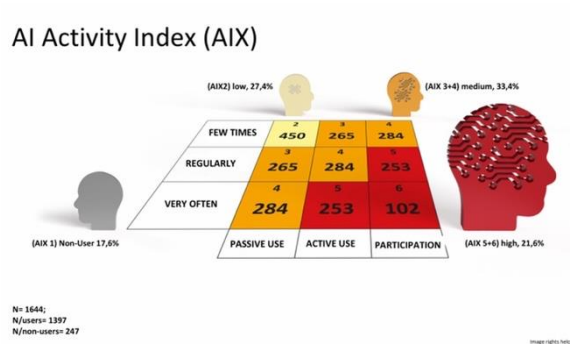


Participants: 1644 people participated in the study, divided into 1397 AI users and 247 AI non-users.

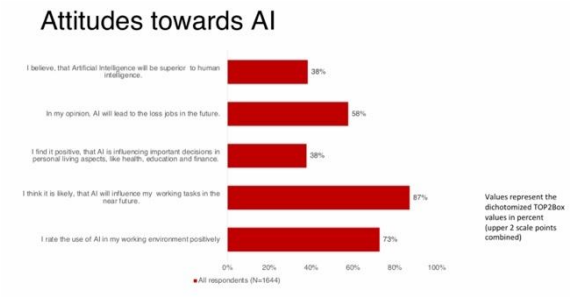


Age structure: In the AIComp study, a broad age structure of the participants was recorded to gain a comprehensive picture of the skills and attitudes towards artificial intelligence (AI) across different generations. The survey included more than 1600 working adults in Germany, focusing on the Baden-Wuerttemberg region. The participants ranged in age from young adults in their early careers to experienced professionals approaching retirement.

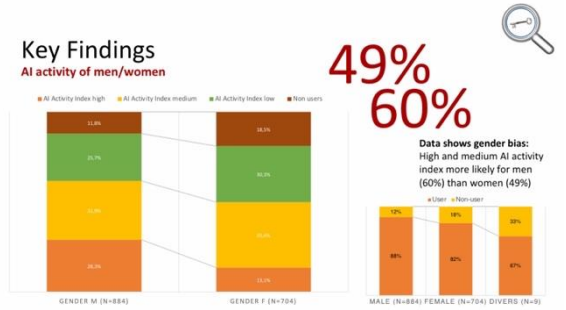
This diversity in the age structure made it possible to gain deeper insights into the different perspectives on and experiences with AI in the world of work and to identify potential generation-specific differences in the perception and adaptation of technology skills. The exact distribution of age groups within the study was chosen to represent the working population in the region studied, which means that the study results offer relevant implications for education and labor market strategies.



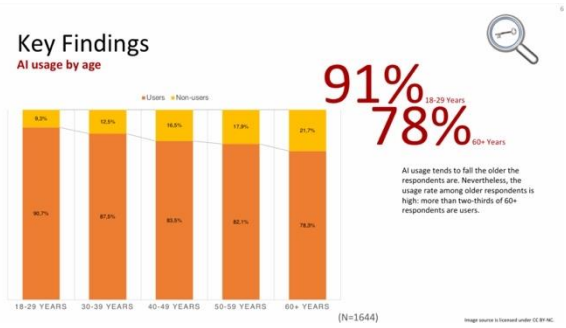
AI activity index: The analysis of the study data enabled the development of an AI activity index (AIX), which combines the intensity of use and the type of use of artificial intelligence in a consolidated measure. This index was successfully applied to all participants in the study. The AIX proved to be a significant predictor of the respondents' assessments of competence and showed a significantly higher explanatory power for these assessments than traditional demographic variables such as age and gender.



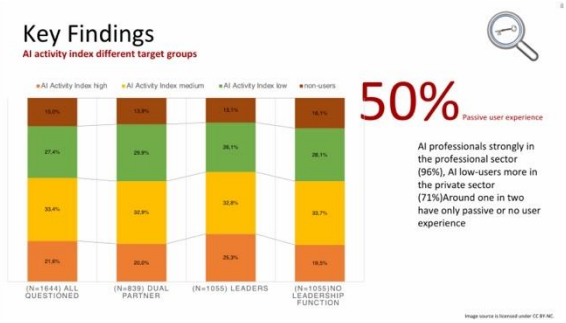
Attitudes towards AI: The AIComp study comprehensively examined attitudes towards artificial intelligence (AI). The results reveal a multilayered picture of the perception of AI among the respondents. While some participants have an optimistic view of the potential of AI to improve work processes and quality of life, others express concerns about data protection, job security, and ethical implications. The study also shows that acceptance of and trust in AI strongly depends on the extent to which individuals feel empowered to deal with AI technologies through education and professional experience. These findings underline the need for companies and organizations to invest in their employees' AI skills development and establish transparent, ethically sound guidelines for using AI to promote trust and positive attitudes.



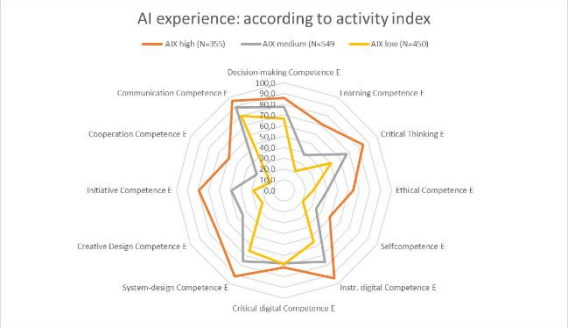
AI gender bias: The data shows a gender bias that parallels the dimensions known in research. High and medium levels of the AI activity index are more likely found in men (60%) than in women (49%).



AI age bias: AI usage tends to decrease with increasing age. While more than nine out of ten respondents in the 18-29 age group say they are AI users, the figure for the 60+ age group is only 78%.

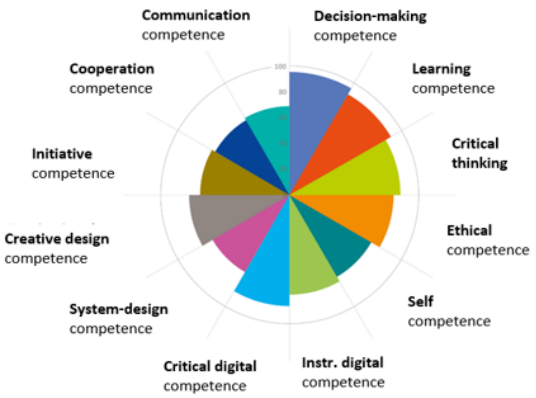


AI activity among different target groups: High levels of AI use are primarily found in the professional sector. The professional environment is thus the primary driver of AI use. Around one in two has only passive or no usage experience.

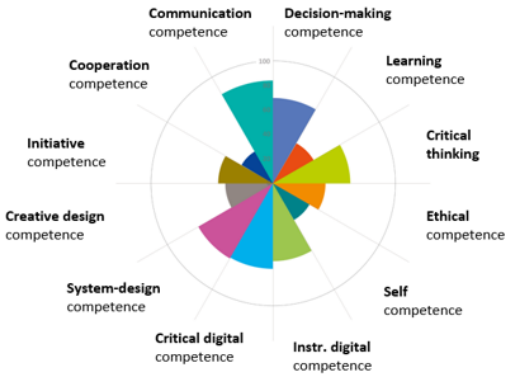


AI experience by activity index: The AI activity index (AIX) is a precise indicator of the accumulation of experience in essential areas of competence that are important for interacting with and using artificial intelligence (AI). The analysis reveals that the AIX plays a prominent role as a predictor variable for the self-perception of AI It has a significantly greater explanatory power than conventional demographic characteristics such as age and gender. In particular, individuals with a high AI activity index are characterized by a pronounced degree of confidence and acceptance
concerning their abilities and sovereignty in dealing with AI-related Future Skills. This suggests that the AIX is an effective measure of people's willingness and ability to successfully face the challenges and opportunities that AI brings. The AIComp study comprehensively assessed current experience with specific skills and their perceived importance for the future. The results reveal a striking discrepancy: while the interviewees unanimously rated the skills under consideration as highly relevant for future requirements, the data also shows that there is significantly less experience with these skills. This skills-experience gap underlines a significant gap between current preparation and the requirements expected due to future developments, particularly in artificial intelligence. The findings thus signal the urgent need to expand and adapt education and further training courses in a targeted manner to bridge this discrepancy and optimally prepare individuals and organizations for the challenges and opportunities of the future

Future significance of future skills



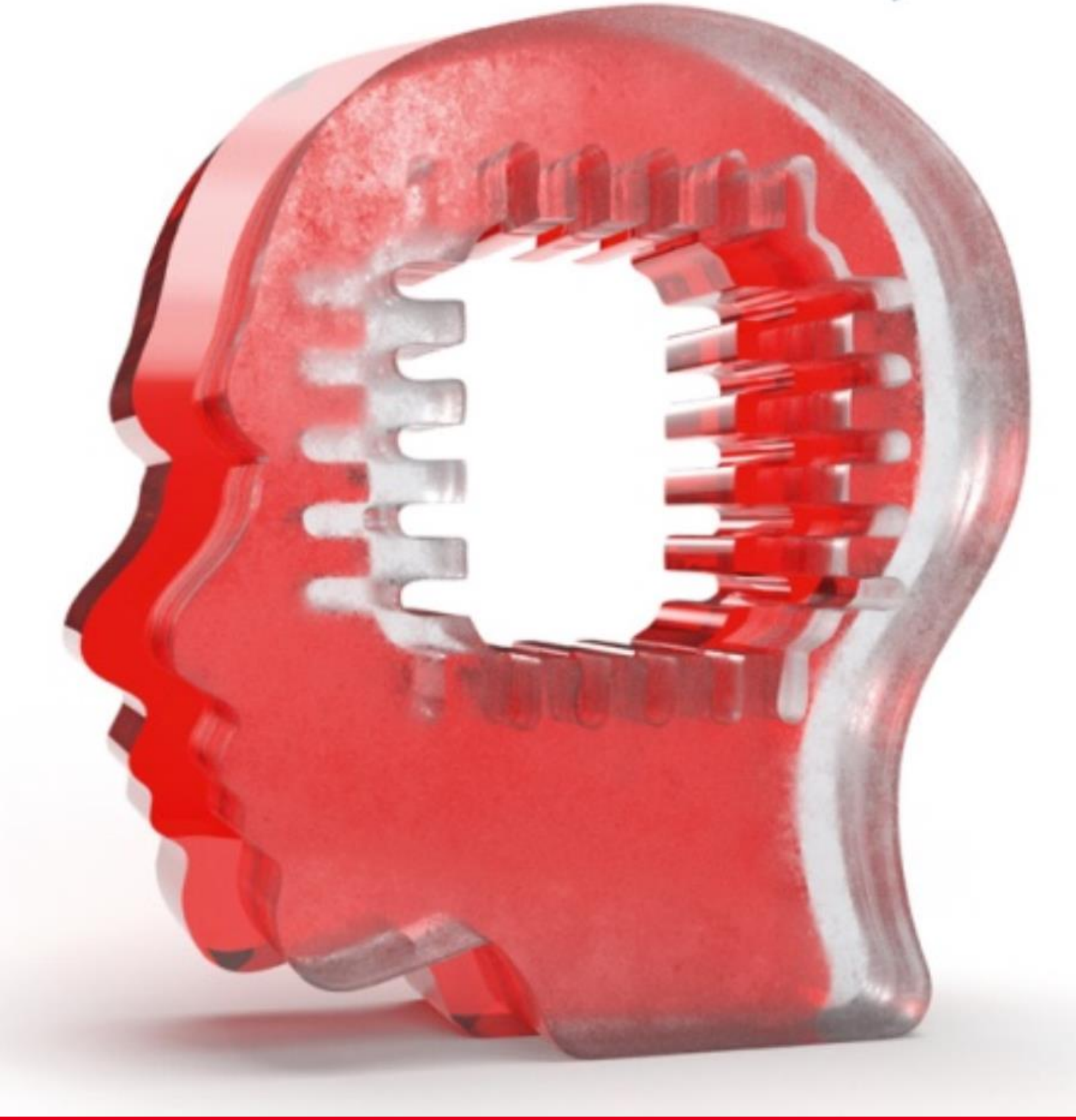
Experience with Future Skills



Values of Questions 5 to 16 on Experience and Future significance of the 12 Future Skills, dichotomized scale, top 2 values, N=1644

Table of Contents

Figures and Tables



1

1. Introduction: Objectives and context of the study

The title of the AIComp study stands for "Artificial Intelligence Competences". The results indicate Future Skills important for a living and working world shaped by artificial intelligence. **This first research report presents the statistical data and results of the AIComp study. The second research report describes the specific AIComp competence model.** The increasing integration of artificial intelligence (AI) into technologies, forms of organization, and processes - both in private and professional life - marks an upheaval in the landscape of skills requirements. Society is on the threshold of an era in which artificial intelligence (AI) will no longer just be a tool for specialists, but an integral part of everyday life and work (cf. Butler et al. 2023). Against this backdrop, the AIComp study focuses on a central question: **What Future Skills are needed to enable people to act effectively in a world increasingly permeated by artificial intelligence and to shape it?** In particular, the study sheds light on skills that go beyond purely instrumental application skills. Given the rapid pace of technological change, job profiles are constantly changing, degree courses and training profiles are reorientated, and AI is increasingly finding its way into the private sphere - often without this being explicitly recognized. At a time when technological innovations are spreading rapidly and bringing social changes that are changing the dimensions of social participation and social inequality, uncertainties also arise. Education plays a decisive role in coping with the necessary technical and social integration process and in enabling people to deal with the realities that lie ahead of them in an emancipatory and creative way. It is crucial to determine the educational goals necessary for this. AIComp provides a building block and orientation for this by researching the basis for the definition of Future Skills in the context of AI.

The **concept of Future Skills** aims to promote the ability to shape both the present, which is already strongly influenced by AI, and a future likely to be even more strongly influenced by AI. This applies to both private and professional life. In our interviews and discussions with citizens, research initiatives, experts, and representatives of political departments, one theme was recurring: The importance of critical questioning and human cooperation in times when machines are developing more and more intelligence. In this sense, the AIComp research project is also a journey into the diverse world of technology acceptance and the different spectrums of opinion associated with it.

The need to deal with AI-related skills arises from a professional perspective and the everyday use of technologies such as voice-controlled assistants, translation software, and intelligent applications. The introduction of generative AI language models, starting with ChatGPT, has transformed the landscape of knowledge work and expanded the relevance of AI skills beyond the circle of specialists. Due to the transformative power of artificial intelligence in all areas of professional and private life, AI-related Future Skills are increasingly becoming the focus of educational processes in all education sectors. They go far beyond purely technical-instrumental competence requirements. Future skills are to be understood holistically in relation to the individual and also include, in particular, requirements for critical-reflective and creative design skills.

The AIComp model, based on the results of the AIComp study, considers skills in this holistic sense. It is about enabling people to move independently and confidently in an environment characterized by AI. This also includes understanding the functions of AI-related systems and being able to use them accordingly. The model emphasizes the importance of critical digital literacy, which goes far beyond the mere understanding of algorithms and machine learning. It is the basis for acting appropriately and competently in specific situations.

The study aims to fully understand the current state of AI experience and the resulting skills people need. This is an essential step on the way to a society in which both individuals and organizations are enabled to master future challenges through the understanding and application of AI. To reach this societal goal, we need empirically based competence models that can serve as orientations for educational processes. By identifying AI-related Future Skills and integrating them into a comprehensive competence structure model, the AIComp study provides a framework for developing strategies to promote these essential competences.

Context of the study

The AIComp study initiated as part of the AI-Campus project (www.ai-campus.org) pursues the ambitious goal of providing a comprehensive empirical basis for the definition and design of the development of key Future Skills to enable the AI-Campus initiative to further develop educational offers in the field of artificial intelligence and thus establish a functional AI competence in society. The project offers a valuable platform to significantly advance empirical research in the field of Future Skills. The study is part of a continuous. This is a comprehensive series of domain-specific studies on Future Skills that have been conducted in recent years as part of the NextEducation research collective (for more information, see www.next-education.org). It integrates existing research results on technology development and acceptance, theoretical frameworks for skills development, and methods of Future Skills research (Ehlers 2022 lists an initial classification of Future Skills methods). The study was conducted by the NextEducation team at DHBW Karlsruhe (www.next-education.org) as an integral part of the joint research project "AI-Campus" (www.ai-campus.org) research project. The NextEducation research collective, which acts as a think tank, is involved in the development of international research and innovation projects in the education sector and is particularly dedicated to the investigation of transformation processes within educational organizations and processes. The "NextSkills 2020" skills concept, which presents 17 Future Skills profiles for the future direction of higher education, recently received international recognition (details at: www.nextskills.org). As part of the AI-Campus project, the AIComp study, which combines qualitative expert interviews with the largest quantitative study in Germany to date, is making a decisive contribution: it is researching the general need and specific requirement profiles for AI skills in the workplace with a particular focus on SMEs and universities in Baden-Wuerttemberg.

Aims and questions of the study

In a world characterized by artificial intelligence (AI), the AIComp study aims to investigate the skills requirements of people who work and live in this world. Against the background of the rapid developments in the field of AI and its increasing integration into all areas of life and work, the study makes a substantial contribution to the development of a deeper understanding of the necessary competences that enable individuals to move confidently and self-determinedly in a society transformed by AI. Specifically, the AIComp study pursues the following goals:

1. Identification of AI-related Future Skills: The study aims to identify key AI-related skills that go beyond technical expertise. The aim is to capture a broad spectrum of skills that people need to be able to actively shape and act responsibly in a world shaped by AI

2. Development of an empirically based competence model: A central aim of the study is to develop a holistic competence model based on the knowledge gained. This model is intended to help shape and support educational processes in a targeted manner to prepare individuals and organizations for the challenges of the future.

3. Establishment of an AI activity index as an indicator of the status of AI transformation: The index is an instrument that allows a differentiated picture of AI activity to be obtained of all respondents, but also of target groups that differ in their social statistical data: for example, by organizational affiliation, by professional position and by areas of activity in the workplace.

4. Determining AI experiences and self-assessments concerning AI: This is about the concrete experiences that respondents have

had with important AI-related skills and their assessment of the relevance of these skills for the future.

5. Promoting AI skills in society: By recording the current state of AI experience and the resulting need for skills, the study creates a basis for developing targeted strategies to promote AI skills. Both individuals and organizations can thus be strengthened through a well-founded understanding of AI and the competent handling of AI.

6. Creating broad access to AI education: As part of the AI Campus project, AIComp is helping to create broad access to AI-related education. By providing resources and learning opportunities, the aim is to enable students, teachers, specialists, and managers as well as all interested citizens to acquire and deepen the necessary AI skills

7. Supporting the transformation of educational organizations: Another goal is to support educational organizations of all kinds in their transformation processes to meet the requirements of a world shaped by AI. The results of the study should help to design educational programs in such a way that they optimally promote the development of the identified Future Skills.

The AIComp study thus not only makes a scientific contribution to research into AI skills but is also intended to serve as a practical guide for the design of educational programs that prepare people for a future that will be increasingly shaped by artificial intelligence.

Artificial intelligence infobox

Artificial intelligence (AI) (in the context of this study) refers to special computer programs that can learn new things independently and make decisions autonomously in complex situations. They are often capable of performances that come close to human intelligence. In many places, computers are already working with such AI components in the background without laypeople noticing. In the AIComp study, we ask about the experiences and assessments of AI applications that respondents perceive and recognize as "artificial intelligence". Examples include ChatGPT or similar applications, the translation program DeepL, image- generating AI tools, but also smart home devices, recommendation systems on the internet and, of course, AI applications in the workplace or in companies.

2

2. The concept of Future Skills in the context of artificial intelligence

2.1 Subject and action theoretical foundations of the competence research approach of the study

Subject- and action- theoretical foundations of the competence research approach of the study

Educational research is attaching increasing importance to the development of skills. This is an expression of the dynamic processes of change to which societies are subject and in which a holistic, future-oriented ability to act is increasingly preferred to the mere accumulation of existing knowledge. The individual is confronted with complex action constellations that need to be shaped productively if risks - such as participation risks (Beck 1986) - are to be avoided. The ability to act in a world characterized by emergent challenges is becoming increasingly important in the field of education. All education sectors are currently under enormous pressure to reform. Action is becoming the central category of endeavors and is gaining conceptual importance over knowledge or reproducible skills. Competence, defined as a disposition to act, is becoming a central element in education systems that must take account of the rapid changes in the labor market, politics, and society. Educational efforts are therefore increasingly required to focus on the promotion of action competence, whereby knowledge and skills play just as important a role as values, motives, and habitual components of personality. Skills development is therefore a holistic process that goes beyond cognitive resources to include values and practical experience. A person, in increasingly episodic and non-standardizable life experiences, becomes the central category. For this reason, action theory and subject-scientific research approaches are of great importance for competence research - as they were also taken as a basis in this study. Our research on competences is therefore based on various theoretical approaches that are based on a holistic understanding of the ability to act. Within the research demarcated in this way, subject-theoretical references (such as approaches based on self-socialization theory) and action-theoretical foundations (such as the habitus approach or that of Bourdieu's capital varieties) have played an increasingly important role in recent years. They focus on the learning subject as an active, productive, selecting, and shaping individual and ask about the conditions for successful action (Zinnecker 2000).

- Pierre Bourdieu's theory is a fundamental point of reference for understanding the significance and anchoring of competences in social theory. The habitus concept plays a central role here, as it makes it possible not only to theoretically understand the profound structure of competences but also to make it empirically tangible. The habitus, a core concept in Bourdieu's theory, embodies the internalized patterns and structures that shape our perceptions, thoughts, and actions. To fully grasp the habitus, however, it is necessary to consider it in connection with other key concepts such as the "practical sense", the "illusion" and the "field", even if a detailed discussion of these concepts goes beyond the scope of this review. In 2021, Timo Bloh took an in-depth look at the connections between competence, habitus, and the concept of education. He sheds light on the complex relationships and demonstrates how these concepts intertwine. Pierre Bourdieu himself developed a profound understanding of practical competence with his praxeological model, which Bloh in detail in 2014 and 2015.

- The bridge between Bourdieu's work and the concept of competence is being built more and more frequently, partly by Bourdieu himself in reference to Chomsky (Bourdieu & Wacquant 2013), but also by other authors. Michaela Pfadenhauer, for example,

sees a "certain proximity" between the psychological concept of competence and Bourdieu's concept of capital (Pfadenhauer 2010). Furthermore, the idea that habitus is not only a condition for professionalization but also plays a central role in the context of the developmental tasks that lead to professionalization, is established in the scientific discussion (Hericks 2004; 2006). Some researchers, such as Martens and Asbrand, even go so far as to consider the habitus as a competence itself (Martens & Asbrand 2009; Martens 2010). Despite these diverse links and approaches, a systematic concept of competence that builds directly on the concept of habitus and can also be placed in relation to current competence models is still lacking. Bourdieu's concept of habitus therefore offers important starting points for a deeper understanding of competence. It acts as a structuring and generative principle that decisively influences our patterns of thought, perception, and action and comes very close to what is commonly understood by competence.

- Following Bourdieu's theory, one could argue that the skills acquired in dealing with AI represent a form of cultural capital that is accumulated and used in a technologically shaped social space. Bourdieu's forms of capital - economic, cultural, social, and symbolic capital - can thus be applied to the area of AI skills. Economic capital can, for example, flow into the acquisition of further training measures or technological tools, cultural capital comprises knowledge and skills in dealing with AI, social capital can manifest itself in networks that arise through the shared use or development of AI technologies, and symbolic capital can arise from the recognition and prestige that individuals receive through their AI expertise.

The agency theory of Erpenbeck and Heyse (Erpenbeck 2012, Erpenbeck & Sauter 2015, Heyse & Erpenbeck 2007) emphasizes the importance of self-organized and value-oriented action in complex situations, which can also be transferred to the field of AI. People with a high level of competence are then able to develop actions to be and remain able to act successfully.

Finally, references to theories of self-socialization (Zinnecker 2000) serve to clarify the self-organization and "agency" with which individuals independently develop their AI skills by actively shaping their development through their interactions with technology and within their social networks and thus acting as producers of their social reality. This perspective emphasizes the active role of the subject in the learning process and their ability to acquire and apply knowledge and skills independently.1

2.2 Competence-theoretical basis for AIComp

[1] Jürgen Zinnecker has summarized the connection between self-socialization and agency as follows (Zinnecker 2000:281.), whereby he relies primarily on the presentation by Krewer & Eckensberg (1991) in the "New Handbook of Socialization Research": "A remarkable and substantial concept of self in this context is that of 'self-development' (Krewer & Eckensberger 1991). It describes the genesis of a central 'center of agency' in the subject. The authors Krewert and Eckensberger combine ideas from cognitive psychology and action theory. At the center of self-development understood in this way is first and foremost the acquisition of the idea of oneself as an actor, i.e. as an acting subject who is responsible for the consequences of one's actions. ... The keywords core self, self-concept, self-esteem and control consciousness refer to concepts that are at the center of current socialization research, insofar as it is inspired by (developmental) psychology." At this point, Zinnecker himself refers to corresponding concepts in Dollase, von Skinner, Chapman & Baltes, Flammer, Bandura and Oerter (for references see Zonnecker 2000). He also quotes Krewer & Eckensberger (1991): The "processing of action experiences" by "a reflective subject as experiencing, planning and acting entity (agency)" leads "to a self-objectification characterized by a cognitive (self-concept), an affective (self-esteem) and a conative (self-confidence, control consciousness) aspect."

Future skills research is competence research. It was McClelland who was the first to call for a focus on skills rather than knowledge in the assessment of learning processes (McClelland 1973). Since then, the concept of "competences" has made an enormous career in both institutionalized and non-institutionalized education.

Since the 1990s at the latest, it has been possible to speak of an emerging skills turnaround in education and training (Davies 2017, Vare 2022). While the focus was initially on teaching so-called "key competences", subject-specific competence frameworks have increasingly been developed since the 2000s (Faulstich-Christ et al. 2010, Spencer & Spencer 1993, Forth 2018). Since the 2010s, many

The new quality of the competence framework is now being implemented by making greater reference to so-called "interdisciplinary competences" in the subject curricula. The importance of action-guiding media skills and digital skills is increasing (Ehlers 2020).

A new development has been observed since around 2015: Subject curricula are now being supplemented by frameworks for "Future Skills", which focus on skills for a constantly changing world (Ehlers 2020, 2022).

The core of the term "Future Skills" is defined in different ways. For our research, we use the definition by Ehlers (2020). He defines Future Skills as competences that enable individuals to act successfully in highly dynamic future and complex problem situations (Ehlers 2020). The new focus of these Future Skills can be applied both to university graduates (Ehlers 2020; Huber, 2016: 106 and 2019: 157; Schlaeger & Tenorth 2020; Wild et al., 2018: 274) and to vocational education and training (Ehlers 2022). This also applies both to German-speaking countries and internationally (Ehlers 2022). It is therefore not enough to simply equate competences with the ability to act, as is often the case. Rather, it is always "a complex structure of dispositions", which, in addition to the skills based on the respective level of knowledge and understanding, also includes the subjective willingness to act - which is "dependent on knowledge, motivation, desire, attitudes, and values" (Ehlers 2020: 112). Whether someone "has" competence is only revealed in their performance, i.e. in the realized, successful action (see Figure 1).

Competence as a triad of knowledge, skills, and attitudes (see Binkley 2012) are the building blocks on which people's ability and willingness to act are based. Competences are dispositions for action (see Fig. 1). Future skills or future competences are those competences that are geared towards specific fields or contexts of action and enable individuals to act in a self-organized and successful manner in a highly dynamic environment. They are based on a foundation of cognitive, motivational, volitional, and social resources and are firmly anchored in the learner's value system. In this respect, they represent competences that have been identified by empirical methods as particularly relevant for future action.

The AIComp study is therefore based on the following definition: "Future skills are competences that enable individuals to solve complex problems in a self-organized manner and to act successfully in highly dynamic contexts. They are based on cognitive, motivational, volitional and social resources, are value-based and can be acquired in a learning process." (Ehlers 2020:57) This has concrete consequences for AI-related competences. For example, "the competence to 'use AI creatively for the further development of one's professional context' is not simply a retrievable skill", but "rather the ability to be able and willing to use AI concepts appropriately in the right situation. Appropriateness is a value-based balancing process." (Ehlers 2023:73)

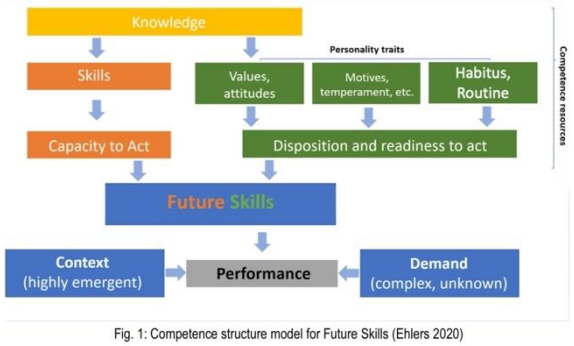


Fig. 1: Competence structure model for Future Skills (Ehlers 2020)

Figure 1 Future skills as competences for action

In this perspective, an individual "competence" therefore does not appear as a mere combination of knowledge elements and individual skills and abilities that can in principle be separated from the respective competence bearer, but as

a holistic disposition to act that is rooted in the respective subject. This means that in the formula "Knowledge, Skills, Attitudes" (KSA), which has become widely accepted (Mulder & Winterton 2017, Binkley 2012), attitudes are not only understood as an individual subjective coloring that must be considered didactically but as the basis of every competence development.

Erpenbeck & Sauter (2015) therefore describe the acquisition of skills as the "integration of rules, values and norms into one's own emotions and motivations", while "at the same time the necessary factual knowledge is acquired" and point out that this requires situational teaching/learning settings. Hartmann & Watling (2022) also emphasize, with specific reference to AI change management in companies, that it is the subjectively experienced values that form the basis for attitudes and attitudes alongside social norms, and that these are decisive for individual and organizational learning, especially in AI-driven change processes.

The NextSkills studies and AICOMP

The NextSkills research project (nextskills.org) has been running since 2016 at the Cooperative State University, the largest university in Baden- Württemberg. It was launched by Prof. Dr. Ulf-Daniel Ehlers and aims to identify models and descriptions for Future Skills using a multimethod research design and international consultations. A model with 17 Future Skills profiles was developed. The concepts presented as part of NextSkills are backed up by in-depth interviews, expert assessments, and international Delphi studies.

About NextSkills: www.nextskills.org

With AICOMP, the Future Skills model is now being further developed in AI-specific questions to identify skills for a world shaped by AI. AIComp is being developed as part of the AI-Cam- pus.org initiative, which is developing a national platform with learning content for AI. All research results will be made available for open access by the NextEducation Group. More information here: www.next-education.org.

About AIComp: www.ai-comp.eu

2.3 On the construction of AI-Comp as a competence structure model

The development of competences is an originally subjective process. This is why the term "competence model" is presuppositional and in need of explanation. However, competence models play an important role in the recording, systematization, and development of competences for institutional educational concepts, e.g. in university departments. Competence models are generally heuristic models. They describe a complex field for a specific purpose in a comprehensible way. They provide a structured framework for describing and organizing the variety of skills, abilities, and knowledge required in a specific context. By differentiating between competences, describing competence characteristics, and tracing competence development processes, competence models also enable a holistic assessment and evaluation of individual and collective abilities (Fleischer et al. 2013).

- Structural models for differentiating content: A competence structure model is a model that is theoretically based on a reflexive (action) competence concept and, starting from this, systematically distinguishes at least three levels: overarching competence areas, several individual competence fields and finally, assigned to each of these, a series of individual competences or competence elements (knowledge, skills or values). Competence structure models focus on the identification, differentiation, and categorization of specific competence dimensions within a field of practice. They ask about the type and number of different competences that are relevant in a particular field. Such models are fundamental to understanding which facets of personal resources such as knowledge, skills, and abilities are necessary to cope with diverse situational requirements (Schaper 2009: 174, Klieme & Leutner 2006: 883). AIComp also sees itself as such a competence structure model: As a result, 12 relevant competence fields were summarized into three large competence areas.

- Level models for the description of competence characteristics: Level models describe different characteristics or levels that a competence can assume. These models aim to segment the competence scale according to the degree of difficulty of a task or challenge and thus provide a detailed insight into the different competence levels. They make it possible to define concrete situational requirements that can be mastered by people at different competence levels. (Fröhlich-Gildhoff et al. 2011: 16). As part of the development of AIComp, the aim is also to develop a *niveau* model.

The choice of a suitable competence model is closely related to the specific objectives of the research project or educational program. While structural models serve to differentiate and structure areas of competence in terms of content, level models offer insights into the different manifestations of competences.

Competence models therefore describe and name ("model") the components of the ability to act. The first competence model of this kind was developed by Boyatzis (1982) for management competences, explicitly drawing on McClelland's influential statement "Testing for competence rather than for 'intelligence'" (McClelland 1973). It was about management competences in
companies,
i.e. interdisciplinary competences with a strong subjective reference that cannot simply be represented as the sum of professional competences (Boyatzis 1982). The Hay Group, a large management consultancy for personnel development, subsequently used this modeling concept successfully with many clients. As a result, the 1990s saw a veritable boom in competence models and competence frameworks, which were specifically designed for the human resource management of large organizations and companies (Spencer & Spencer 1993, Lucia & Lepsinger 1999, cf. the summarized overview in Stricker et al. 2020).

With the Bologna Process at the latest, new requirements were also placed on universities: The "Competence Turn away from what is taught, with a focus on curriculum content, to what is learned" (Vare 2022) led to in Europe in particular, this has led to a continuing conjuncture of the concept of competence in vocational training, higher education and general education (lifelong learning). The theoretical foundation for this comes primarily from educational psychology, vocational education, and higher education pedagogy (cf. Weinert 2001, Winterton et al. 2005, Klieme et al. 2006, Mulder et al. 2006). The activities and programs of the EU have an important pacemaker function. They have led to the DigComp competence framework, which has also included 73 AI competence items since version 2 (from 2022)

3

3. Research methodological design

AIComp follows a mixed methods approach. Both method triangulation and data triangulation were used to gain a broader and deeper understanding of the research topic:

- Desk research on the current state of research: an overview of relevant theoretical concepts and existing empirical studies;
- qualitative consultation of numerous experts and practitioners from the respective specialist or application area, as strictly structured surveys of a larger group and/or as semi-structured qualitative interviews;
- quantitative survey of as many representatives of the target groups as possible;
- multivariate analysis of the data. In such a process, a coherent model is developed step by step that meets the criteria: intrinsic coherence, the right level of concreteness/generality, the precision of definitions, practical relevance, and concrete usability. This is "art and science" at the same time, as the title of the book by Lucia & Lepsinger (1999) on the development of competence models says. To end up with a validated competence model that is suitable as a basis for concrete strategies for higher education and continuing education, we have structured the procedure for the AI-Comp study as follows:

Preliminary study (see chapter 4):

- Literature analysis and determination of the state of research concerning AI skills
- Inventory of competence items from elaborated competence models ("behavioral anchors") in an item pool
- Consolidation and quality check of the competence items
- Formulation of the first version of the AI Comp model
- Qualitative review of the first version of the AIComp model (semi-structured interviews)
- Formulation of a second version of the AI comp model as a result of the qualitative interviews

Quantitative Studie (vgl. Kapitel 5)

- Construction of the questionnaire
- Implementation of the study
- Evaluation of the data
- Formulation and publication of the AIComp model

The AIComp framework is a contribution to societal transformation, towards a world in which citizens can develop freely and actively. An understanding of skills that is limited to economic and technical aspects would be too narrow for this. This is why AIComp is based on a concept of human capital that includes social and cultural capital in addition to economic capital (Bourdieu 1983). Holistically understood education is human capital in this broad sense. It not only plays a decisive role in economic performance but also the general development of individual and social potential.

With this objective in mind, the AI-Comp study aimed to identify Future Skills that are not only important for certain professional or specialist fields of action but for a wide range of challenges that many different people are confronted with. It is therefore about behavioral, holistic handling skills. Subject-specific skills that are only useful in a narrowly defined field of action are put aside here.

The aim of the qualitative preliminary study was not to achieve completeness, but rather comprehensive content coverage. The central qualitative criterion here was construct saturation, intending to identify new competence items until there was a sufficient level of coverage concerning the constructs covered interpersonally comprehensible saturation. This endeavor led the research team to a repeated iteration of mutual assignment processes, as envisaged by the qualitative content analysis procedure.

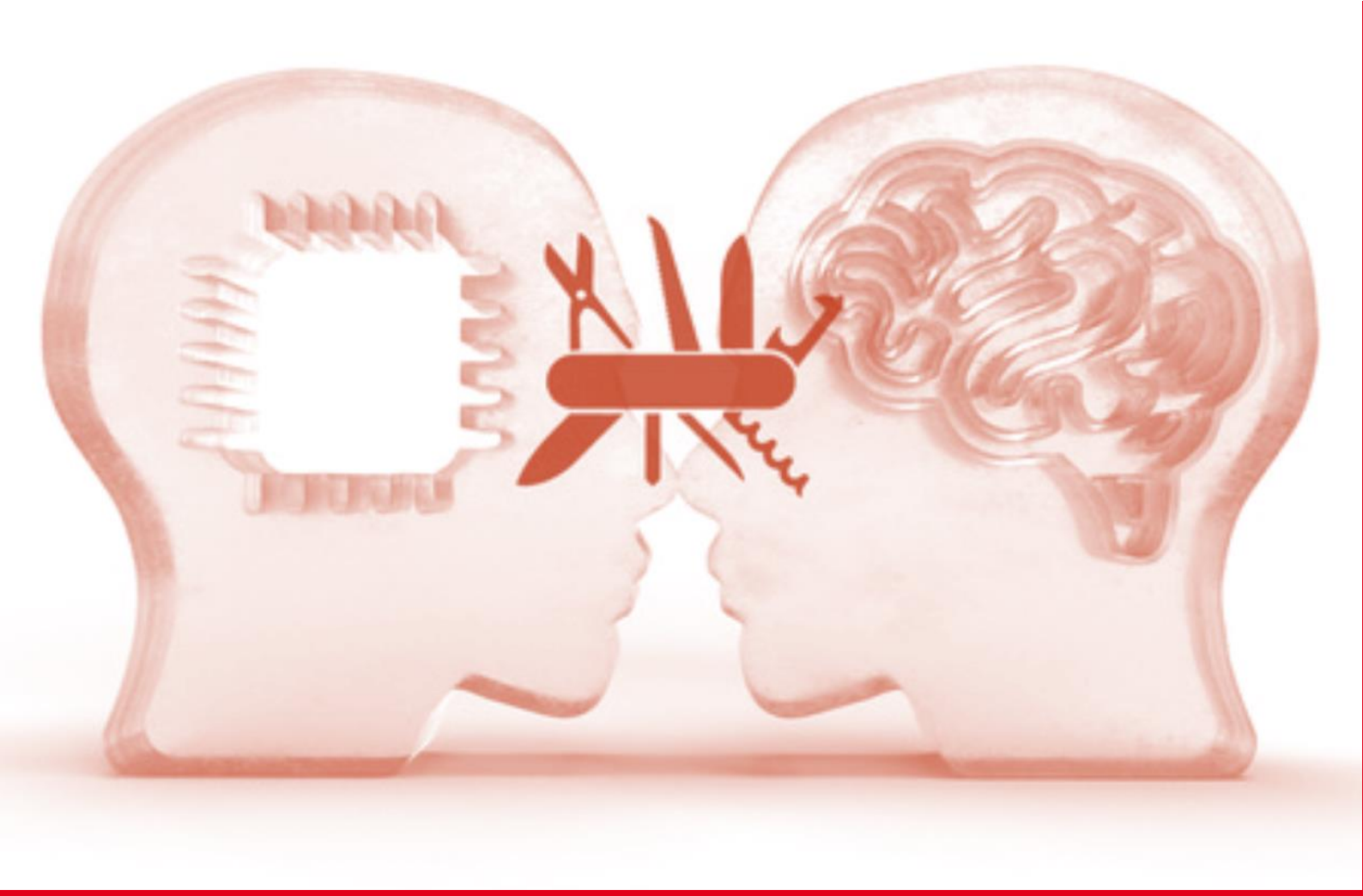
To achieve the broadest possible coverage in the competence items, the criterion of maximum differentiation was also used. International competence studies as well as domain-specific competence studies and studies from

different areas of education were included. The intention behind this maximum differentiation of the study area was to map the structures found as comprehensively as possible by considering a diverse study landscape and thus to cover a broad subject area.

The "Rapid Evidence Assessment" (REA) method was chosen for the individual subphases of the preliminary study. The aim was to obtain a systematically comprehensible and representative overview of the entire spectrum of studies, papers, and written concepts on the topic of "AI competences" in an agile process. This methodical approach made it possible to systematically develop a broad spectrum of competence items that reflects both the depth and breadth of the field of investigation and thus lays the foundation for further research in this innovative and increasingly important area of higher education.[2]

In addition to reconstructing the various terms and approaches for describing "AI competence", the specific goal was to create an inventory of concrete competence items for the field of AI from existing competence lists or frameworks (see "Research questions") to then identify the structures and needs behind the confusing and hardly predictable AI transformation in the further sequence of qualitative and quantitative research steps. The preliminary study was conducted by a research team between December 2022 and February 2023.

[2] As part of a well-reflected heuristic approach, the FGD method accepts compromises in the completeness of coverage and the depth of penetration of a field (cf. Barends, Villanueva et al. 2017). FGD is often used by decision-makers to get a quick overview of a particular field, which can then guide future activities. The FGD guideline of the Center for Evidence-Based Management (CEBMa) suggests 12 steps to follow when conducting FGD phases (Barends, Rousseau et al. 2017, see https://cebma.org/).



4

4. Preliminary study: Evaluation of the state of research in relation to AI - competences

4.1 Rapid evidence assessment as a method for determining the state of research

There are different types of literature reviews. The most widespread method for presenting the state of research on a topic is the so-called systematic review (SR). An SR aims to identify all relevant studies on a specific topic as comprehensively as possible and to select suitable studies based on explicit criteria. These studies are then evaluated to determine their internal validity. A systematic approach is taken when selecting the studies: The methodological quality of the studies in question is evaluated independently by several researchers using explicit criteria. An SR is therefore transparent, verifiable, and reproducible. As a result, the probability of bias in an SR is significantly lower than in conventional literature reviews.
A Rapid Evidence Assessment (REA) is also an evidence overview. The main difference between these two types of reviews is the time and resources devoted to their production, as well as the breadth and depth of the results. To be "fast", an REA makes concessions to the breadth, depth, and completeness of the search. Certain aspects of the search can be restricted to achieve a faster result for example:

- Search: Consultation of a limited number of databases and exclusion of unpublished research.
- Inclusion: Inclusion of only certain research designs (e.g. meta-analyses or controlled studies).
- Data extract: Only extract of a limited number of key data such as year, population, sector, study design, sample size, moderator/mediator, main results, and effect sizes.
- Critical evaluation: Limiting the quality assessment to methodological appropriateness and quality.

Due to these limitations, an FGD can be more prone to bias than an SR. However, an SR usually requires several months (sometimes even more than a year) of work by a team of scientists, as it aims to identify all relevant published and unpublished studies, whereas an REA can be conducted by experienced individuals in just a few weeks. As a rule, organizations have neither the time nor the financial resources to commission a team of scientists to conduct an SR. Therefore, an FGD is the most widely used method for reviewing the scientific literature.
The following 12 steps were carried out in the qualitative preliminary study, as described in Table 1. As part of our empirically based and tightly timed research project, the initial aim was to understand the range of relevant approaches as part of a reflective heuristic approach and to collect as many competence models as possible with precisely listed individual competence items from different areas. New publications on the topic of "AI and competences" are currently appearing all the time. The AIComp study aimed to identify and examine, from a subject-scientific perspective, the fundamental areas of competence that are not themselves directly affected by the rapid innovation of specific AI technologies and applications.

Table 1 Procedure for the preliminary study in 12 steps according to the FGD model

Nr.	Name & Description	AIComp-Procedure
1	Background: Determines the co text for the study.	Identify approaches to describe and inventory "competences for AI" from the research literature.
2	Question: Specifies the objectives for the study.	Objective: To obtain a comprehensive picture of the range of approaches to "competences" in the field of AI, to develop an inventory list of competence items and to organize these in the form of a competence structure model.
3	Inclusion criteria: Filters which evidence should be included (e.g. date, type, focus area, etc.).	Criteria for the relevance of studies and approaches: time (2019 to May 2023), language (German, English), keywords (artificial intelligence and abbreviated AI, and the following combinations, with and without hyphen: AI and competence, AI and competence framework, AI and skills, AI and abilities, AI and learning, AI and education, AI and training, AI and learning objectives, as well as English equivalents, in particular AI competences, competences, literacies).
4	Search strategy: Identification of database searches, publications	Multidimensional search process: Internet search engines, meta-databases, journals, conference reports. Iterative, snowball-like reference search including gray literature.
5	Study selection: Abstract review; full-text reading for those that meet the inclusion criteria. criteria	The search focused on elaborated competence frameworks with lists of specific competence items. Furthermore, publications that explicitly deal with the concepts of "AI literacy" or "AI competence" but do not themselves contain lists or elaborated frameworks were classified as relevant.
6	Data extraction: Extraction of all relevant data and results from the evidence base	Extraction of the "competence items" from the developed AI competence models and creation of a list with 157 competence items.
7	Critical evaluation: application of quality metrics; critical interpretations	Qualitative content-analytical reduction of the item pool. Review of the scope and quality using a test-based assignment of 34 competence items to the four competence dimensions (see below).
8	Results: Results of the evidence assessment. Tensions in the evidence base are highlighted	Further reduction of the item base from 157 to 83 items by checking and filtering the items for their relationship to the competence dimensions of knowledge, skills and attitudes. Elimination of items that are purely descriptive or overarching in nature.
9	Synthesis: summarizing the evidence and constructs; main findings on research questions.	Deductive development of competence fields with the data: Structuring of the item pool of 83 competence items based on 17 profile fields of the NextEducation model. First (1) Assignment of items to competence fields. All items could be assigned to 13 competence fields. Then mutually related development of new or modified designations of the competence fields based on the content characteristics of the items while retaining the structuring by the competence fields of the NextEducation model. Result: 13 competence fields with a total of 83 competence items.
10	Conclusions: Concise statements that convey the main results.	Development of comprehensive competence field designations and, in some cases, necessary internal structuring for some competence fields. Result: Formulated description and systematization of AI-related competences.
11	Limitations: Description of the limitations of the FGD method for this study.	Limitations in the construct clarity of the competence field formulations were examined using qualitative interviews. The focus and coverage of the competence items were also investigated.
12	Practical implications: Recommendations for action.	Development of a qualitatively based action-theoretical competence model, at the same time the basis for further quantitative research steps.

REA Step 1 and 2: Background and question (see explanation above in Table 1))

REA Step 3 to 6: Literature research and data extraction

The literature search was designed as a multidimensional search process. Internet search engines, meta-databases, specialist journals, and conference reports were used. An iterative, snowball-like approach including gray literature ensured holistic coverage of the research spectrum. The focus of the search was on the first version of the AIComp competence framework was developed with lists of specific competence items. Furthermore, publications that explicitly deal with the concepts of "AI literacy" or "AI competence" but do not themselves contain lists or elaborated frameworks were classified as relevant and included in the development of the first version of the AIComp competence model. The results summarized:

- Ten papers address AI-related skills from different perspectives and with differ-

ent scopes: elaborated competence frameworks, lists of competence elements, studies as a basis for the development of such frameworks, and general discussions of the concept of "AI competences" or "AI literacy".

- Four publications were identified that contain suitable lists of specific AI competence items and are not limited from the outset to university degree programs or specific job profiles: Long & Magerko 2020, Vuorikari et al. 2022, André et al. 2021, Laupichler et al. 2023a. A further framework with AI competences was only announced and initially only documented in a web article (then published in September by the Bertelsmann Foundation: Cantakli & Puntschuh 2023). The Concordia University AI competence framework was excluded because it is aimed at curriculum development and cannot easily be related to the practical needs of working people and the interesting framework of the UNESCO Broadband Commission, which adds some formulations of AI competences to the list of digital competences of "public servants" with a leadership function, but which are too job-specific and at the same time too general in relation to AI to be meaningfully included in our inventory of "AI competence items".

- Only one of the competence models found is, therefore, itself a complete competence structure model in the sense described above: the DigComp model, which the EU has developed to describe the necessary digital participation competences of citizens (for the theoretical basis, see Ferrari 2013, Vuorikari et al. 2016). In 2022, the latest version, DigComp 2.2, was expanded to include 73 AI-specific competence items.

- Long & Magerko (2020: 2) define "literacy" as "a set of competences that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home and at work". Laupichler et al. 2023 make Long & Magerko's list the starting point for their own Delphi study. André et al (2021) speak explicitly of "skills", but deliberately refrain from defining skills themselves. They too are initially very pragmatically concerned with the needs of users, in this case specifically with "AI-supported technical and production work" in companies

Table 2 Results of the literature research and evaluation

Nr.	Titel	Author	in the inventory included	Year	Sector
1	What is AI Literacy? Competences and Design Consideration	Long, Magerko	x	2020	not specified
2	Competences for AI. Changes, needs, options for action	André et al.	x	2021	VET
3	AI Literacy: Definition, Teaching, Evaluation and Ethical Issues	Ng, Leung et al.	not included, no list included ten	2021	not specified
4	Artificial Intelligence Competence Framework. A success pipeline from college to university and beyond. (Concordia University, Kanada)	Blok, Trudeau, Cassidy	not included because no suitable List	2021	Higher Education
5	Artificial intelligence and AI-related skills. A research overview.	Sūna/ Hoffmann	not included, no list included	2021	not specified
6	A.I. and Digital Transformation. Competences for Civil Servants	UNESCO Broadband Commission	not included, since no suitable Item list	2022	VET
7	EU DigComp 2.2: The Digital Competence Framework for Citizens	Vuorikari, Kluzer, Punie (EU)	x	2022	LLL
8	AI Literacy: Competence dimensions and influencing factors in the context of work	Wienrich, Carolus et al.	uses list of Long & Magerko	2022	VET
9	MAILS - Meta AI Literacy Scale: Development and Testing of an AI Literacy. Questionnaire Based on Well-Founded Competence Models and Psychological Change- and Meta-Competences	Carolus et al.	used list from Long & Magerko	2022	VET

10	Delphi study for the development and preliminary validation of an item set for the assessment of non-experts' AI literacy	Laupichler et al.	x	2023a	not specified

After selecting the research literature, a systematic inventory of competence items was carried out to develop an in-depth understanding of the competences required in dealing with artificial intelligence (AI). This process involved the careful analysis and extraction of specific behavioral anchors from various AI competence models that reflect the range of skills (knowledge, skills, and values) required to act competently in AI contexts. The result was a list of 157 individual competence terms.

During extraction, generic terms and categories of the underlying competence models were excluded to generate the broadest possible pool of items that had not yet been pre-structured as the basis for an unbiased analysis. These items describe behavioral anchors in a relatively broad spectrum: from differently specified cognitive abilities (e.g. understanding, knowing, being able to describe; rather general in Long & Magerko (2020), more concrete in DigComp 2.2, more granular in Laupichler et al. (2023a) via the naming of complex actions (e.g. André et al. (2021): "skills in analyzing large data sets" and "data mining") to quite generic action competences (e.g. André et al. (2021): "are able to adapt to the opportunities and challenges implied by AI and adapt their way of working accordingly").

REA Step 7: Qualitative content-analytical reduction and verification of the quality of the item pool based on four competence dimensions

The third step was to check the quality of the item pool and improve it where possible. The competence item pool was then subjected to a content review: Do these items in their entirety represent the whole spectrum that belongs to a holistic understanding of subject-related action competence? It had to be ensured that the items in the item pool covered all important dimensions of action and did not, for example, focus too much on the instrumental handling of AI tools. Finally, the competence formulations used originate from approaches with very different theoretical foundations and pragmatic requirements. The "Bielefeld Media Competence Model" by Baacke (1996, 1997, 2001) was used for this study. From an overarching perspective, it describes four fundamental dimensions of an emphatic, holistic ability to act in relation to digital media, "which in principle every person should have developed" (Hugger 2021: 4). The context of Baacke's model was the media landscape of the 1990s, but the competence concept formulated here has subsequently been referred to digital media again and again, most recently by Hugger (2021). AI applications and AI environments can therefore also be understood as extensions of these digital media: They are "media" as "AI applications" in the sense of extensions of human agency (McLuhan 1964). In the background, AI has become an increasingly important component of media technologies such as search engines, recommendation systems, and "social media", and the new "generative AI" is now also producing independent entities that produce and distribute media content.

The "Bielefeld Competence Model" comprises four dimensions: (1) practical application (2) cognitive skills ("knowledge"), (3) creative design skills, and finally (4) critical-reflexive skills. The dimension "critical ability" refers comprehensively to the ability to differentiate, evaluate, and assess technological applications and their effects on oneself, the social world, and the objects of the world. On the cognitive level, it is about concrete knowledge about the use, effect, and function of media technologies and media instances. Active and creative design with media and for media can be understood here in the sense of design thinking: the ability to think differently about existing technologies and tools and to contribute to creatively adapting, changing and further developing them.

The review of the item pool according to this criterion revealed that a total of 34 items can be assigned very well and without overlap to these four dimensions of acting with technical media (as tools as well as production instances of media content). These 34 items are listed in table form below. The English-language formulations in Long & Magerko (2020), Vuorikari et al. (2022), and Laupichler et al. (2023a) were translated into German as literally as possible. The

respective competence dimension is highlighted in color:

Table 3 Structured collection of the most important competence items ("behavioral anchors")

Nr.	ID	Category	Source (abbreviation)	Behavior anchor / competence description
Practical application skills: Ability to use AI in a differentiated and targeted manner and to use AI tools and concepts for to make it available and usable for your own objectives.				
1	KIA1	Experience-related application dimension (being able to use)	André	Has the skills to work confidently and confidently with traditional digital media and technology and can work smoothly with common AI applications and office programs and digital collaboration technologies. They have sufficient awareness of digital security aspects.
2	KIA2	xperiential application dimension (being able to use)	André	Are proficient in relevant programming languages such as Python as a basis for machine learning.
3	KIA3	experiential application dimension (being able to use)	André	Have skills in managing, collecting, compiling, processing and modeling data.
4	KIA4	experiential application dimension (being able to use)	EU	Is open to using AI systems that support people in making informed decisions in line with their goals
5	KIA5	experiential application dimension (being able to use)	EU	Can actively decide whether they want to follow an AI-generated recommendation or not
AI customer: Knowledge and discernment with regard to AI and AI application concepts as well as knowledge of important application areas.				
6	KIW1	cognitive knowledge dimension ("being knowledgeable")	EU	Has a willingness to continually learn, educate themselves and stay informed about AI (e.g., to understand how AI algorithms work, to understand how automated decision making can be biased, to distinguish between realistic and unrealistic AI, and to understand the difference between Artificial Narrow Intelligence, i.e., current AI capable of narrow tasks, and Artificial General Intelligence (AGI), i.e., AI that surpasses human intelligence, which is still science fiction).
7	KIW2	cognitive knowledge dimension ("being knowledgeable")	Long	Recognize and describe examples of how computers think and make decisions.
8	KIW3	cognitive knowledge dimension ("being knowledgeable")	Long	Recognize that computers often learn from data (including the user's own data).
9	KIW4	cognitive knowledge dimension ("being knowledgeable")	André	Have the necessary subject-specific knowledge/skills to perform day-to-day tasks appropriate to their position. Depending on the employee's position, this may also include manual skills, for example.
10	KIW5	cognitive knowledge dimension ("being knowledgeable")	André	Can recognize processes and workflows in the company, think in terms of these processes and workflows and structure their own work behavior in terms of processes and workflows.
11	KIW6	cognitive knowledge dimension ("being knowledgeable")	Laupichler	Can describe risks that can arise when using artificial intelligence systems.
12	KIW7	cognitive knowledge dimension ("being knowledgeable")	Laupichler 130	Can name ethical issues in connection with artificial intelligence.

13	KIW8	cognitive knowledge dimension ("being knowledgeable")	Laupichler 143	Can explain why data security must be considered in the development and use of artificial intelligence applications & explain why data protection must be considered in the development and use of artificial intelligence applications.
14	KIW9	cognitive knowledge dimension ("being knowledgeable")	Delphi 145	Can give examples from his/her daily life (private or professional) in which I could come into contact with artificial intelligence.
15	KIW10	cognitive knowledge dimension ("being knowledgeable")	EU 211	Is aware that digital tools (including AI-driven ones) can contribute to energy efficiency (e.g. by monitoring heating needs at home and optimizing heating management). (4.3)
16	KIW11	cognitive knowledge dimension ("being knowledgeable")	EU 229	Knows how to formulate search queries to achieve the desired result when interacting with conversational agents or smart speakers (e.g. Siri, Alexa, Cortana, Google Assistant), e.g. by recognizing that the query must be unique and spoken clearly for the system to answer it in order for the system to respond as desired.
17	KIW12	cognitive knowledge dimension ("being knowledgeable")	EU	Is aware that AI systems are usually developed by people from narrow demographic backgrounds (e.g. white males from higher socio-economic groups in higher income countries), which may result in the systems they develop being less sensitive to the needs of women, people from different ethnic minorities, lower socio-economic groups, people who need digital accessibility (e.g. with disabilities, functional limitations), or citizens from low-income countries.
18	KIW13	cognitive knowledge dimension ("being knowledgeable")	EU	Knows that all EU citizens have the right not to be subject to fully automated decision-making (e.g. if an automated system rejects a credit application, customers have the right to request a review of the decision by a person).
AI creativity: Creative design skills, using AI tools and developing them further to innovatively design concepts, processes or organizations.				
19	KIK1	creative dimension	Long	Decide when the use of AI is appropriate and when human skills should be used.
20	KIK2	creative dimension	André	Can contribute to teams with different compositions. They can work together with colleagues from different professional backgrounds and with different levels of experience and expertise. In contact with customers and users of AI systems, employees can explain the special features of the use of AI systems for their respective area of responsibility.
21	KIK3	creative dimension		Ability to use AI creatively in and for strategy processes and leadership concepts.
22	KIK4	creative dimension	André	With management responsibility - can organize a team, coordinate and delegate tasks (bundles). They can communicate the potential and limitations of AI, allay fears and activate further training potential. When integrating AI systems into company processes, they can formulate reasonable goals and thus help shape the change process.
23	KIK5	creative dimension	EU	Considers the ethical implications of AI systems throughout their lifecycle: this includes both the impact on the environment (ecological consequences of the production of digital devices and services) and on society (e.g. platformization of work and algorithmic management that may suppress workers' privacy or rights, the use of devices that may violate workers' privacy or rights, the use of cheap labor for labeling images to train AI systems).
24	KIK6	creative dimension	EU	Is interested in experimenting with different types of AI systems depending on their own personal needs (e.g. virtual assistant, image analysis software, voice and facial recognition systems, autonomous cars, "embodied" AI such as robots).
Critical, analytical attitudes and value-based positions that enable students to take a critically differentiated, analytical and reflective approach and adopt an ethically based perspective on the topic of AI.				
25	KIR1	Critical analytical dimension (reflexive)	Long	Critically analyze and discuss the characteristics that make an entity "intelligent," including a discussion of the differences between human, animal, and machine intelligence.
26	KIR2	critical analytical dimension (reflexive)	Long	Identify types of problems where AI excels and those that are more challenging for AI.

27	KIR3	critical analytical dimension (reflexive)	André	Can critically interpret and evaluate the information and results of AI systems. can independently and competently assess when trust in AI systems and the data generated by AI systems is justified.
28	KIR4	critical analytical dimension (reflexive)	Laupichler	Can critically reflect on the possible effects of artificial intelligence on individuals and society.
29	KIR5	critical analytical dimension (reflexive)	EU	Recognizes that AI tools for creating images, writing and music are dependent on humans (e.g. in setting the initial parameters and selecting the results), while humans can use AI tools to enhance their creativity.
30	KIR6	critical analytical dimension (reflexive)	EU	Can recognize that some AI algorithms can reinforce existing views in digital environments by creating "echo chambers" or "filter bubbles" (e.g. if a social media stream favors a particular political ideology, additional recommendations can reinforce that ideology without being confronted with arguments to the contrary).
31	KIR7	critical analytical dimension (reflexive)	EU	Weighs the benefits and risks before allowing third parties to process personal data (e.g. recognizes that a voice assistant on a smartphone used to give commands to a robot vacuum cleaner could give third parties - companies, governments, cybercriminals - access to the data).
32	KIR8	critical analytical dimension (reflexive)	EU	Is aware that the data on which AI depends may contain biases. If this is the case, these biases can be automated and exacerbated by the use of AI. For example, search results about occupations may contain stereotypes about male or female occupations (e.g. male bus drivers, female sales clerks).
33	KIR9	critical analytical dimension (reflexive)	EU	Recognize that the application of AI systems in many areas is usually uncontroversial (e.g. AI that helps to avert climate change), but that AI that interacts directly with people and makes decisions about their lives can often be controversial (e.g. software for sorting CVs in recruitment processes, scoring of exams that can determine access to education).
34	KIR10	critical analytical dimension (reflexive)	Long	Understand that data cannot be taken at face value and must be interpreted critically.

REA Step 8: Content-analytical reduction of items

The item base was further examined using content analysis. This enabled a further reduction of the item base. This was done in two substeps:

- A qualitative content analysis review of the items and the consolidation of the items from different sources to create a clear and unambiguous "item library". Items with sufficient similarity were combined, synonymous expressions were further merged, and multi-dimensional items were broken down into their components.
- A further reduction of the item base by checking and filtering the items for their relation to the competence dimensions of knowledge, skills, and attitudes. Eliminating items that are purely descriptive or too general.

The result was a list of 83 one-dimensional items with no overlaps in content.

REA Step 9 and 10: Deductive development of competence fields for AI Future Skills from the item pool

In principle, various approaches are conceivable for moving from an unstructured list of competences to a competence structure model. For example, structuring according to content-related topics (inductive) is conceivable, e.g. on a semantic level, i.e. grouping similar competence items into semantic clusters of competence terms.

A second, deductive approach was chosen for the development of the AI-related skills structure model AIComp. The NextSkills model (Ehlers 2020) served as the initial basis. The NextSkills model divides general Future Skills, i.e. not yet AI-related Future Skills, into 17 skills fields, which are grouped into three skills areas (ibid.).

The NextSkills model was reviewed again in 2022 to ensure that it can cover the skills lists available in German-speaking countries at that time and that these can be incorporated into the complete NextSkills structural model. The resulting scientifically sound conceptual and

analytical framework comprises 17 fields of action ("Future Skills Profiles") that will be particularly relevant in the future.
The 83-item AI item pool was therefore used to check whether and, if so, which of the
17 competence fields are suitable for structuring the competence items. Here, too, it was confirmed that the pool is suitable for deriving a comprehensive range of competences. In this way, an initial compilation of 13 "Future Skills" emerged, which appeared to be particularly significant as "action skills for a world shaped by AI". 11 of the 13 "Future Skills" competence fields could be assigned between 2 and 5 AI competence items. In the two more technology-related competence fields

As expected, there were significantly more "digital competence" (19) and "system competence" (13). In addition to semantic and content-related structuring, this also provides a depth of action theory, which results from the fact that competence profiles are already formulated holistically in terms of action theory, while items often only refer to individual aspects of competence.
A categorization was constructed along the lines of content-related semantic and learning theory aspects, which led to 13 competence fields. The competence fields were named and described in a new or modified way according to their substantive content.

REA Step 11: Validation of the first AI comp version through qualitative interviews
In a further construction step, qualitative interviews were conducted to validate the plausibility of the construction, the relevance, and the comprehensibility of the formulations for the competence fields and competence areas. The interviewees were selected according to the criterion of maximum differentiation - both in terms of their biographical age, their perspective on the topic, and their experiences.
Ten semi-structured interviews, each lasting 30 minutes, were conducted for this purpose. This methodological approach aimed to obtain context-specific knowledge in a targeted and comparable manner, while at the same time responding flexibly to the individual experiences and perspectives of the interviewees. (Ehlers, Lindner, Rauch 2023) The interview guidelines had a three-part structure:
(1) First, questions were asked about the general context and the individual understanding of artificial intelligence (AI). (2) Then, open questions were asked about necessary AI competences from the interviewees' point of view, in connection with their experiences in their areas of activity. (3) Finally, the first version of the AI comp framework was presented as a graphic, gone through with the interviewees, and asked for critical feedback based on the previous conversation.
The interview results were documented in a data entry form to enable a systematic comparative analysis of the qualitative and quantitative data. These results were coded according to the main statements. A list of the main topics that the interviewees had named or raised in the interview was compiled. These results were incorporated into the further research process in duplicate form: The semi-open survey provided indications of the respective range of AI experiences at work and in private life and how each was interpreted individually. These results later served as the basis for the creation of the 44 AI-related questions in the quantitative study questionnaire. The structured feedback from all interviewees on the first draft of the AIComp competence model was used for basic validation and targeted further development.
The competence model based on the Next Skills framework was unanimously rated as fundamentally suitable by the interviewees and led to productive comments on the competence topic in each case. The competence model was fundamentally revised based on the analytical findings and the respondents' specific suggestions for changes. The basic architecture was retained, but individual structural elements were supplemented or summarized. Some areas of competence were named and defined differently, and some descriptions were clarified and modified.
Particularly, AI-related "digital competence" was further differentiated into two separate areas of competence: "instructive digital competence" and "critical digital competence". In the sense of Baacke's concept of "critique", the latter concerns the ability to perceive AI systems in a differentiated way and to see through them as transparent. Overall, this resulted in the first,

qualitatively validated version of the AI-related AIComp model, which now comprised 12 fields of AI-related competences. This version then served as the basis for the quantitative part of the study.

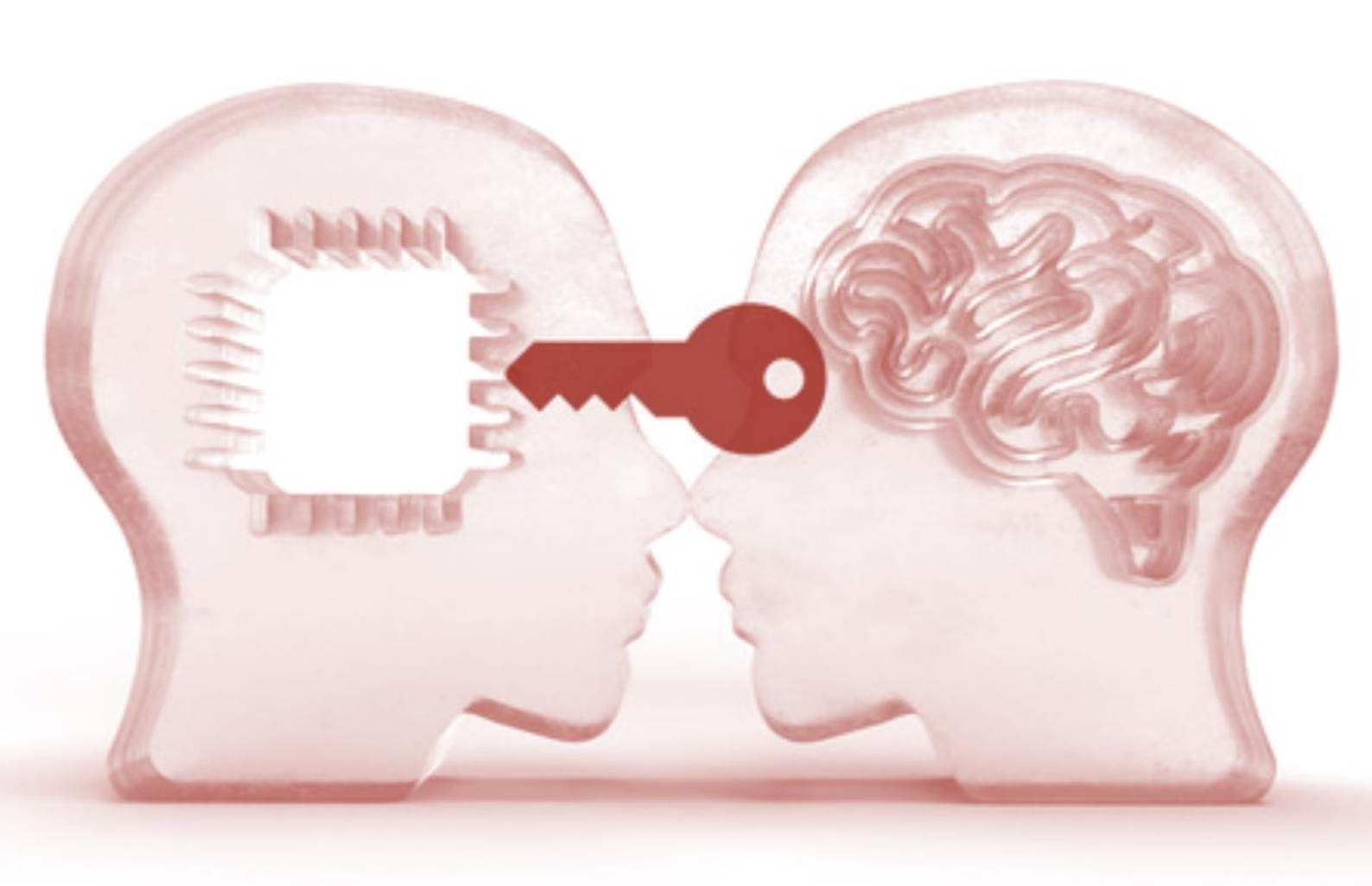
4.2 Consolidated areas of expertise for AI-related Future Skills

After reviewing the state of research on "AI competences" and the qualitative interviews, a competence structure model was developed that is already divided into three large competence areas, each with 12 assigned competence fields:

A. Developing your skills for AI-related areas of activity: Skills to act confidently as an individual in an AI-permeated world and to use AI concepts and tools responsibly and reflectively for their own goals.
B. Working and designing with AI and for AI: Skills to use AI applications and to (further) develop them for organizationally or individually significant contexts of action.
C. Shaping your social environment with and for AI: Competences to use AI appropriately in one's own private or professional social environment and to creatively design new AI-related areas of activity in collaboration with others.

The 12 fields of competence assigned to these three major areas are described as follows:

A.I **Decision-making Competence:** Be able to weigh up choices in AI-dominated spaces, make decisions, and take responsibility for them.
A.II **Ethical Competence**: The ability to perceive and understand AI-relevant issues as ethical issues and to act responsibly in relation to them.
A.III **Learning Competence**: Openness, ability, and willingness to learn about AI topics using AI tools and applications.
A. IV. **Critical Thinking**: Be able and willing to reflect on the underlying behaviors, mindsets, and value systems in AI-influenced action spaces and evaluate how they influence actions and decisions.
A.V **Self-competence**: Being able to find a balance between self-determination and heteronomy in AI-influenced spheres of activity and to use AI tools for self-directed support.
B.I **Instrumental digital competence:** Being able to use and further develop AI tools and knowing the limits of AI applications.
B.II **Critical digital competence:** Understanding, analyzing, and critically evaluating the technological logic of AI systems regarding their impact on data, organizations, and society.
B.III **System design competence:** Ability to align AI-integrated concepts and/or systems with personal, psychological, and social needs, both in the planning and deployment phases.
B.IV **Creative design competence**: The ability to develop future designs for AI-related action spaces in organizations and to solve complex problems by combining technical and human systems.
C.I **Initiative Competence**: Open, courageous, and creative participation in initiating and shaping joint AI-related action spaces (professional and private) in one's environment.
C.II **Cooperation Competence**: Being able to work on AI projects and plans in interdisciplinary cooperation projects, also across cultures.
C.III **Communication Competence**: Ability to communicate about AI topics in different contexts and to understand different perspectives empathically.



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5. Quantitative study on Future Skills for a living and working environment influenced by AI

This section describes the operationalization, design, and implementation of the quantitative online study AIComp. The initial vision of the competence model developed after the previous steps formed the basis for the development of a questionnaire that was to be designed to appeal to different people from all socio-demographic groups and all areas of work. All employed persons in Baden-Wuerttemberg were defined as the target group.

Of the 44 questions in the main questionnaire, which forms the core of the study, eight questions related to the specific use of AI (at home and work) and to general assessments of AI technologies in general. This was followed by three questions on each of the 12 fields of competence of AI-Comp. A total of 41 questions Assessment questions: here, statements were given that could be agreed upon on a four-part rating scale.

- Part 1: Your experiences with AI and attitudes towards AI (8 question items on type and frequency of use, general attitudes towards AI)
- Part 2: Your skills in dealing with AI (36 question items on the competence fields, described here as "12 skills that are useful in dealing with AI").
- Part 3: Statistics (5 questions on socio-demographic data: Age, gender, occupational function, field of activity, company size)

5.1 Questionnaire construction

The questionnaire comprised 5 sections, which are shown in Fig.2:

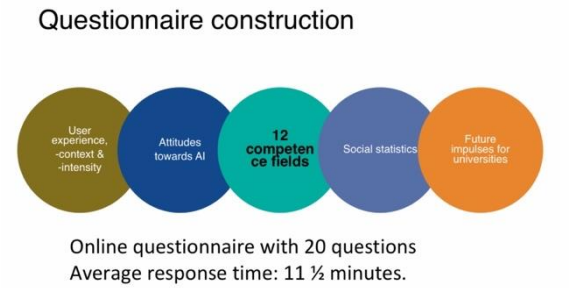


Figure 2 Structure of the questionnaire: Sequence of topics asked about

In the main section with the questions on the competence fields, three assessment questions were asked for each competence field, corresponding to three dimensions (Figure 2):

- A question about self-perceived sovereignty concerning these skills (i.e. the degree of competence that one ascribes to oneself);
- a question about their assessment of the importance of these skills in the future;
- a question about their experience with AI that requires these skills.

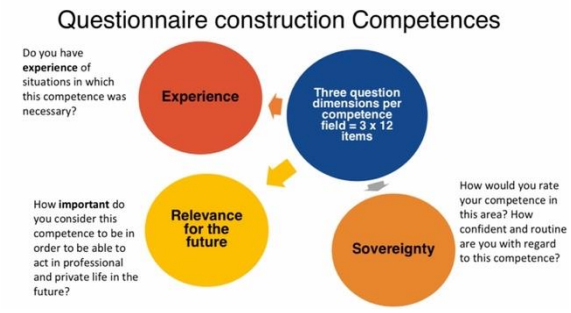
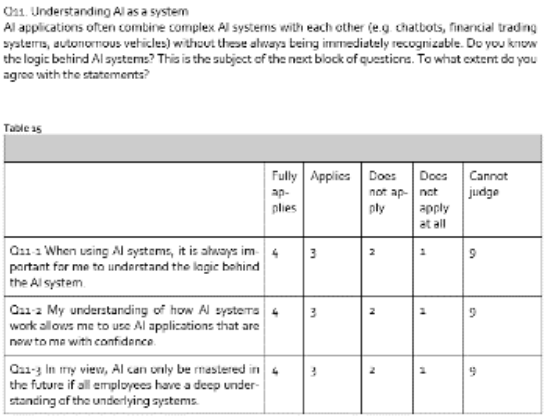


Figure 3 The three question dimensions for each competence field

The study used Likert scales with four-part ratings for all questions on the AIComp model and for five other questions on AI assessment. In each case, a statement was provided to which respondents could respond with "strongly agree", "agree", "disagree", "strongly disagree" and "can't judge". The system of questions on the three dimensions, together with the Likert scaling, opened extensive possibilities for the differentiated recording and analysis of the responses. AI-related attitudes and self-perceptions of the participants.

Figure 3 shows the example of the three AI-related questions on what was called "Critical Digital Literacy" in the underlying AIComp model:



Q11. Understanding AI as a system
AI applications often combine complex AI systems with each other (e.g. chatbots, financial trading systems, autonomous vehicles) without these always being immediately recognizable. Do you know the logic behind AI systems? This is the subject of the next block of questions. To what extent do you agree with the statements?

Table 15

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q11-1 When using AI systems, it is always important for me to understand the logic behind the AI system.	4	3	2	1	9
Q11-2 My understanding of how AI systems work allows me to use AI applications that are new to me with confidence.	4	3	2	1	9
Q11-3 In my view, AI can only be mastered in the future if all employees have a deep understanding of the underlying systems.	4	3	2	1	9

Figure 4 Example of question formulations with Likert scale

In addition, a filter was used for a separate section to address some questions specifically to the employees of the DHBW's[3] dual partners. These are related to the requirements of the dual partner organizations concerning studying and preparing for AI. Finally, socio-demographic data was collected, including information on the profession, the activity at the workplace, and the size of the respective company or organization.
The aim of the entire survey was twofold:

- To collect data that would enable the preliminary AIComp model with 12 competence fields to be statistically validated, multivariate analyzed and thus provide precise information for further development;
- to obtain as broad and meaningful a picture as possible of the subjective AI-related skills assessments of the employees surveyed in Baden-Wuerttemberg.

5.2 Field access, data collection, and data analysis

Field access was via an online questionnaire developed using Titian's ESF Survey system. The pretest took place in May 2023 with over 120 people and led to the further development and validation of the questionnaire. The field phase lasted from May 15, 2023, to July 31, 2023.
In principle, every person with a job in Baden-Wuerttemberg belonged to the target group. The study was primarily sent out via a multiplier procedure: the invitation to participate in the survey was distributed to many thousands of the more than 9,000 dual partner organizations (of all sizes) via the 10 regional DHBW locations and their partner management. DHBW professors, especially course directors with their partner contacts, were included both as multipliers and as a target group. In addition, the Chambers of Industry and Commerce in Karlsruhe and Heilbronn as well as Südwestmetall supported the mailing via their communication channels.
At the same time, a social media campaign was run on various channels over the entire period, supported by a specially developed graphic series. The university management and the DHBW staff council expressly supported the study as partners.
All in all, we estimate the following campaign reach:

- Direct mailings (estimated): 5500
- Professors reached: 900
- Social media reach: 22000
- Distribution of the study via newsletters and partner websites (IHK and Südwestmetall): 3500
- Total: 31900
- Participants in total: 6653
- Response rate: 20.86%
- Usable questionnaires after data cleansing: 1644

Response rate after data cleansing: 5.15%
According to this estimate, the campaign reached a total of over 31,900 people, with 6,653 participants taking up the invitation to take part in the survey and viewing at least the first page of the online survey. This would correspond to a gross take-up rate of 20.86%. After data cleansing, 1,644 questionnaires were

[3] The students of the Baden-Württemberg Cooperative State University are sent by more than 9000 partner organizations. These include companies and organizations of all sizes and sectors.

usable, resulting in an adjusted net response rate of 5.15%.[4] This rate is of sufficient quality for open online surveys. The data cleansing included the inclusion of questionnaires that were answered up to and including question 16 (1,745 questionnaires) and the exclusion of questionnaires with conspicuous data patterns (feeders) as well as questionnaires with contradictory information (101 questionnaires).
The data collected in this way cannot be considered representative of the population, as no comparative data is available for the population of all employees in Baden-Wuerttemberg with AI experience. However, there is a constructed representativeness concerning age and gender in relation to the structure of employees in Baden-Wuerttemberg.

The evaluation was carried out in the following steps:

I Analysis step 1: Univariate and bivariate analysis

The first phase of the data analysis comprised the univariate and bivariate evaluation of all questions concerning age, gender, position, and organizational affiliation.

II Evaluation step 2: Construction of an AI activity index

An AI activity index was developed based on answers to questions relating to the frequency (question 2) and type of AI use (question 3).

III Evaluation step 3: Attitudes towards AI

The evaluation of the main statements on attitudes towards AI formed the third step.

IV. Evaluation step 4: Explorative evaluation

In this step, a statement system was developed for the main statements and trends, which was then discursively refined and validated by the research team.

V. Evaluation step 5: Evaluation using principal component analysis

For the further construction of an updated competence model, we were able to draw on a total of 59,184 individual subjective assessments of AI-related competences. A principal component analysis was used to construct and compare different variants of the competence model with 4 to 12 factors (i.e. data clusters indicating separable competence fields). A 12-factor solution was ultimately selected based on statistical indicators (scree plot) and quality of content. This means that the AIComp model again shows 12 areas of competence after the statistical test. The explanatory power of the Future Skills approach has been confirmed. However, the structure of the responses has resulted in new divisions and attributions in some places (see the separate report on the details of the AIComp skills model development).

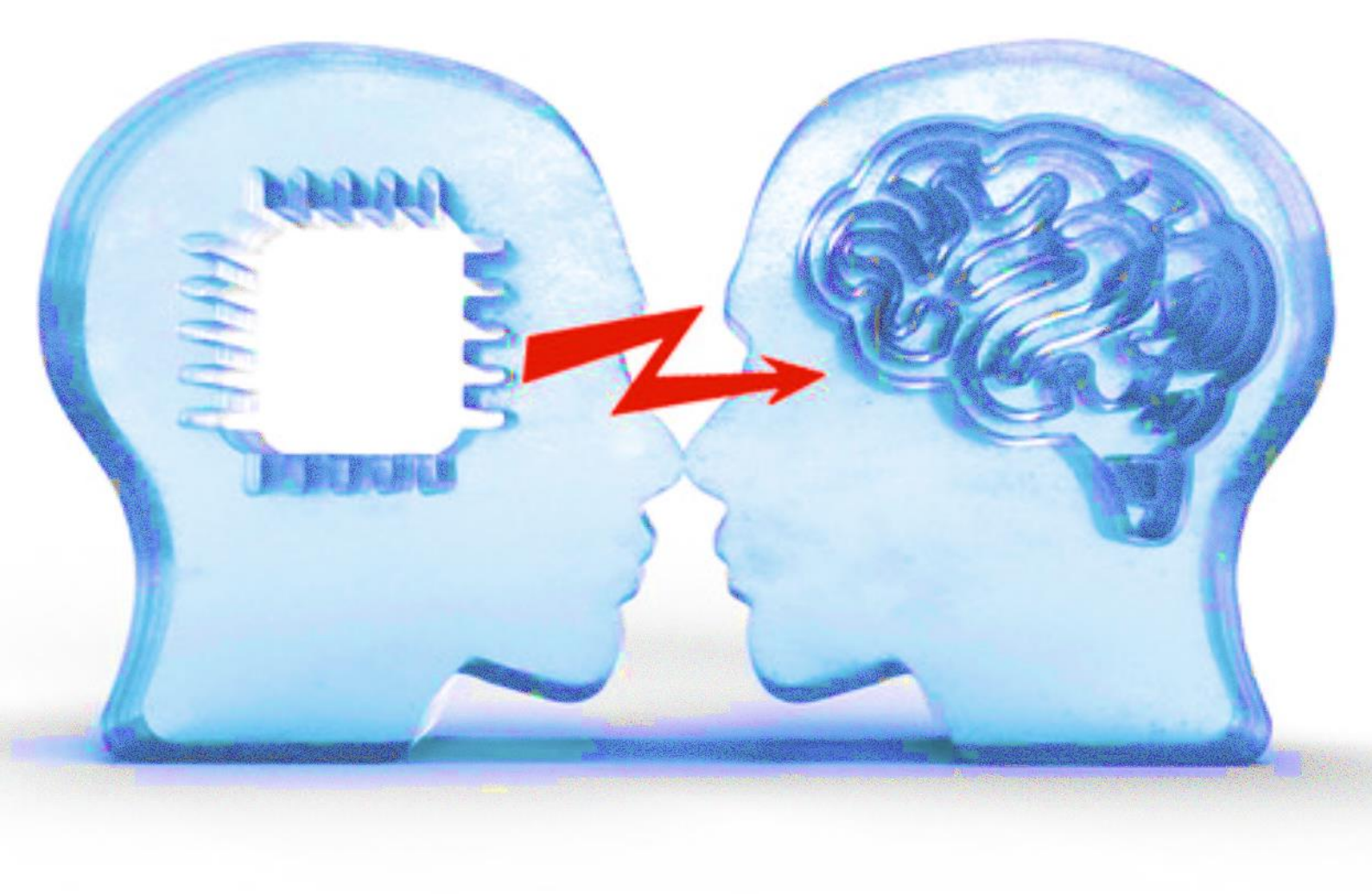
VI Evaluation step 6: Explorative target group analysis

In addition to the explicitly queried target group characteristics, an explorative analysis was carried out using the data from all responses to the competence field questions, which led to the identification of a total of four clusters using a screen test and a scatterplot-based cluster analysis. After all, almost exactly half of the participants who use AI could be assigned to one of these four clusters, which represent user types based on the competence profile. (The results of this exploratory target group analysis will be published separately).

VII Evaluation step 7: Action relevance matrix

Finally, a discrepancy analysis was carried out, which evaluated the 36 competence field questions in two matrices: To assess the future significance of the 12 competence fields by the respondents, the values for experience and then the values for sovereignty were each compared separately (see below, 5.5).

[4] Values are partly estimated.



6

6. Results of the quantitative study

6.1 Description of the study sample

Our research shows that of the 1,644 participants in the study, 1,397 people reported using AI applications, while 247 people reported being non-users. This differentiation between users and non-users not only allows us to analyze social statistical characteristics in-depth but also usage behavior concerning AI technologies. The results provide valuable insights that can support the development of inclusive strategies to ensure that no one is left behind in the digital transformation.
We must take these non-users with us to ensure a socially responsible digital future. Their inclusion is not only a question of digital participation but also social justice. By understanding their needs, fears, and reservations, we can develop more targeted programs and initiatives aimed at overcoming these barriers. This can be done through education, making technology accessible, and creating awareness of the benefits of digital applications.

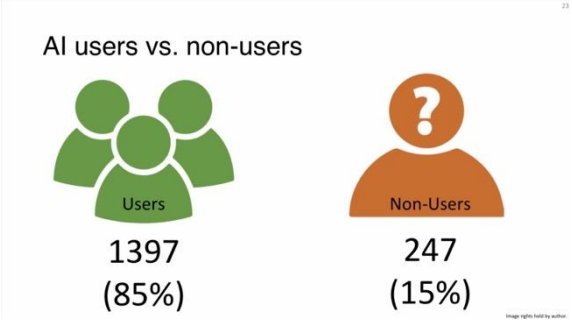


Figure 5 AI users vs. non-users

6.1.1 Age structure

The age structure of the study participants reflects a broad spectrum of the working population. The age distribution among the 1,644 participants can be characterized as follows (Figure 5)):

- Under 18s: At just 0.1% (n=1), the group of under-18s is virtually unrepresented. This is in line with expectations - this age group is usually not yet fully employed.
- 18-29 years: The younger working people aged 18 to 29 make up 20.3% (n=334) of the sample. This age group is particularly interesting as they encounter new technologies at an early age and could therefore potentially have a higher affinity for AI applications.
- 30-39 years: People aged 30 to 39 years represent 23.3% (n=383) of the participants and thus represent the early to mid-career phase.
- 40-49 years: The 40-49 age group is represented by 21.4% (n=352) and reflects the established working population.
- 50-59 years: With a share of 23.7% (n=390), the 50-59 year-olds form the largest group in the study. This age category includes experienced workers who hold important positions and functions in organizations.
- 60+ years: Participants over the age of 60 makeup 6.4% (n=106) and re-represent the group of older employees or those in transition to retirement.
- No information: A small proportion of respondents (4.7%, n=78) did not provide any information about their age.

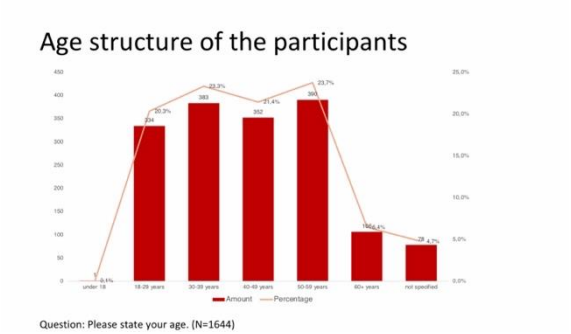


Figure 6 Age structure of the participants in the AIComp study

The age distribution shows a relatively even representation of the different age groups in working age. The mean age of the participants is 41.6 years, the median is 41 years. The age distribution is therefore slightly skewed to the right, with most respondents in middle age.

This corresponds quite closely to the age distribution in the last Baden-Wuerttemberg microcensus.
This data provides important indications of the potential of different age groups to engage with AI technologies. They can serve as a basis for the targeted development of education and development programs that address the specific needs and abilities of these age groups.

6.1.2 Gender balance

The gender distribution of the 1,644 participants was also surveyed as part of the study. The distribution by gender is as follows (Figure 6):

- Female: 704 people identified themselves as female, which corresponds to 42.8%. This high level of participation opens the possibility of analyzing gender-specific data from the study concerning the use of AI by women in more detail.
- Male: Most participants, namely 884 people or 53.8%, stated that they were male.
- Diverse: A small number of respondents (9 people, corresponding to 0.5% of participants) identified themselves as diverse.
- Not specified: 47 people, or 2.9% of participants, did not specify their gender.

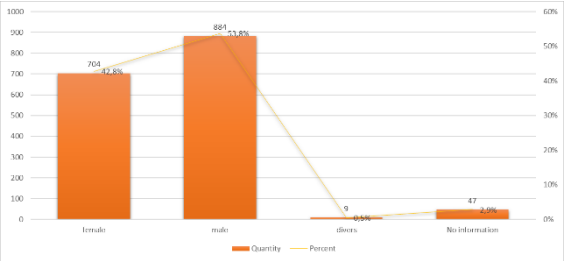


Figure 7 Gender distribution of participants in the AIComp study

The gender distribution in this study is important for the interpretation of the results regarding gender-specific differences in the use of and attitudes toward AI. The gender ratio in the random sample is also very close to the gender ratio of employees in the 2021 Baden-Wuerttemberg microcensus (54% to 46%). The imbalance between male and female participants is slightly higher in the random sample with a difference of 11 instead of 8 percentage points.[5]

6.1.3 Organization size

The size of the organizations in which the participants are employed provides a significant clue to differentiate the experience with and attitude towards AI (Figure 7). The question arises as to whether a larger company size brings with it a higher affinity for AI and how this presents itself in the context of SMEs.[6]
As part of the survey, the question was asked: "How large is the organization to which you feel you belong?" The distribution resulting from the random sample differs significantly from the overall statistics for Baden-Wuerttemberg: there is a disproportionate number of employees from large companies (250 employees or more) and significantly fewer from small and medium-sized enterprises according to the EU definition of SMEs (10-49 employees). In contrast, the proportion of employees from medium-sized companies (50-249 employees) corresponds approximately to the national average.

[5] In the 2021 microcensus, the gap between men and women was 7.3 points (Statistisches Landesamt Baden-Württemberg 2021); among the participants in the study, it was 10.9 points.

[6] The IfM Bonn (Institute for SME Research) uses its own, expanded definition of "Mittelstand" to fill the large gap that opens up between an SME with 249 employees and large corporations with many 10,000 employees: https://www.ifm-bonn.org/definitionen/mittelstandsdefinition-des-ifm-bonn

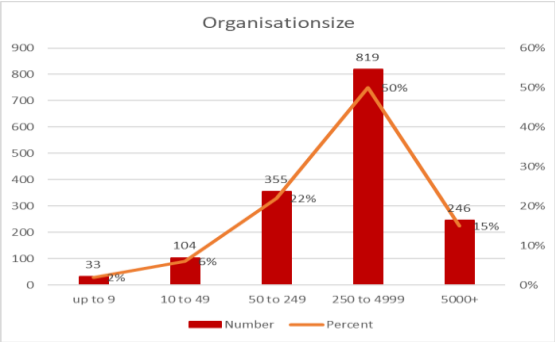


Figure 8 Size of the organizations in which the participants in the AIComp study work.

The company size classes were adjusted for a more differentiated evaluation. Companies with 50 to 249 employees are considered "medium-sized enterprises" according to the EU definition, while all companies with more than 250 employees are classified as "large enterprises". To better reflect the "large SMEs", which are economically important for Baden-Wuerttemberg, a separate category was created for organizations with more than 250 employees. 2250 to 4999 employees. Employees in this category represent the largest group in the sample at around 50% (819 people). A focus group thus emerges that includes employees from "large, medium-sized companies" and "small, large companies". The entire "Mittelstand" also includes the second-largest group with 355 people from companies with 50 to 249 employees, i.e. "medium-sized companies" as defined by the SME definition. A further 246 people (approx. 15%) work in large companies with 5,000 or more employees. Micro-enterprises with up to nine employees account for only approx. 2% (33 people) and only 104 people (approx. 6.3%) are employed in small companies according to the SME definition (10 - 49 employees).

The study shows in many places that the type and intensity of experience with AI strongly depend on the size of the company. Interestingly, only 15% of participants have no AI experience at all. Deviations from this average mainly affect employees from small companies, which have around 5% fewer AI users than the average, and from large companies with more than 5000 employees, where the proportion of AI users is around 8% higher than the average).

These findings indicate that there is fertile ground for the adoption and application of AI technologies, especially in large and medium-sized companies in Baden-Wuerttemberg. The so-called "hidden champions", often medium-sized companies that are global leaders in specific niches and represent a mainstay of Baden-Wuerttemberg's economy, are particularly present. Company size appears to be a predictive factor for AI affinity, which points to the need for a differentiated consideration of different company sizes in the context of AI integration.

6.1.4 Professional position of the participants

Of the 1,644 respondents, most could be categorized into specific, clearly defined professional roles (Figure 8). The following professional positions, which account for more than 5% of the total responses, are particularly noteworthy:

- Team leader: With 184 mentions, which corresponds to 11.2% of the total participants, this group represents the largest share in the professional classification.
- Manager: This category comprises 171 people or 10.4% of respondents, which indicates a high proportion of people in management positions.
- Personnel officer: With 151 responses and 9.2% of the sample, HR specialists are also well represented.
- Project manager: This role was indicated by 108 participants, i.e. 6.6%.
- Engineer: As representatives of the technical professions, engineers are involved with 92 mentions (5.6%).
- Managing director: This management level is represented with 90 mentions, corresponding to 5.5% of responses.
- Lecturer: Teaching and research staff is also a relevant group with 88 responses or 5.4%.
- IT specialist: People from the IT sector accounted for 85 responses, which corresponds to 5.2% of participants.

  In addition, there were 104 participants (6.3%) who did not specify their professional position.

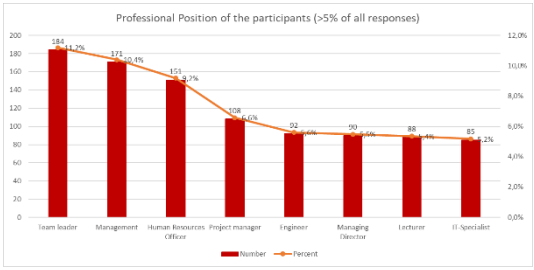


Figure 9 Occupational positions of the participants in the AIComp study.

In addition to these defined categories, 277 responses (16.8%) were recorded under "Other professional position (less than 5%)" and 294 responses (17.9%) under "Other professional position (free text)". These categories cover a variety of professional roles that were not broken down in detail in the study but represent a significant spectrum of the professional landscape.

Occupations from the technical sector: 92 people from the engineering sector and 197 IT professionals, to which 49 (3%) software developers can be added.

Professions from the education sector: 225 from the higher education sector (plus 15 who stated "professor" in the free text), 165 (plus 22) from other educational professions, particularly from continuing vocational training.

In addition, there is a group of 30 people with social work professions who were most likely reached as participants via the DHBW faculty.

The wide spread of professional positions in the sample shows that AI is a topic that is of interest across all hierarchical levels and subject areas. In particular, the strong representation of managers and specialists in the sample could indicate an increased awareness and active engagement with AI technologies in these professional segments. These findings are important to understand how AI is perceived and used at different levels of the professional hierarchy and to develop targeted strategies for the further training and implementation of AI in companies.

Barely represented in this random sample are liberal professions, creative professions, healthcare professions, teachers, and blue-collar professions.

6.1.5 Fields of activity of the participants

The AIComp study also asked about the participants' fields of activity across all professions and thus offers important insights into the world of work in the context of the AI transformation. The predominance of activities that can be classified as knowledge work or management is clear in this sample: The areas of higher education and science, IT and mathematics as well as the education, training, and library complex are particularly strongly represented - i.e. precisely those fields that will be captured and significantly influenced by AI development at an early stage. The following picture emerges in detail (Figure 9):

- Universities and science: With 225 mentions (13.7%), the academic sector proves to be strongly involved in the use and development of AI. At the same time, this group is also central to research into new AI technologies and contributes to the development of theories and the scientific understanding of AI.
- IT and mathematics: 197 mentions (12.0%) in this area underline the importance of expertise in information technology and mathematics for AI development. These specialists are often directly involved in the development of algorithms and the implementation of AI systems.
- Education, training, and library: 165 mentions (10.0%) in this field make it clear that the training of specialists and the transfer of knowledge about AI play a key role. This sector is crucial for training the next generation of AI experts.
- Office and administration: With 158 mentions (9.6%), the potential for the use of AI to increase efficiency and automate routine tasks is also evident in administrative activities.
- Management & consulting as well as business operations and finance: Both areas, with 109 mentions each (6.6%), indicate that managers and financial experts are increasingly using AI to make strategic decisions and optimize financial processes.
- Architecture and engineering: 96 mentions (5.8%) in this technical field show that AI also plays a role in planning and construction to solve complex problems and develop innovative solutions.

Together, these seven areas of activity account for around 64% of all responses. Including related activities, which in themselves account for less than 5% or were additionally mentioned in the free text, they even represent three-quarters of all explicit mentions.

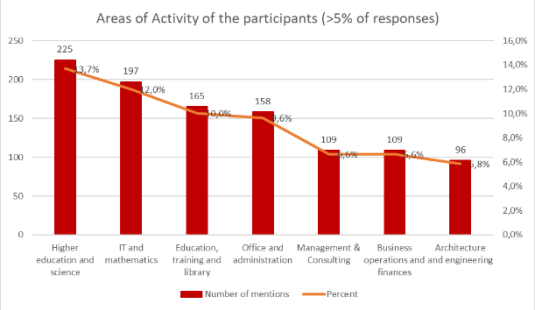


Figure 10 Fields of activity of the participants in the AIComp study

This can be summarized in three major areas of activity for which the data from the study can be used to conclude the status of AI transformation among employees:

- Around 24% of mentions fell into the field of education, with higher education and science as the dominant subcategory.
- Around 23.5% of participants work in the field of technology, particularly in IT and engineering.
- 23.5% of responses provided more detailed information about the field of organization. Management, administration, and finance are most strongly represented.

The study reveals that the areas of activity mentioned - education, technology, and organization - are central sectors of knowledge work that are most influenced by AI technologies. These areas are crucial both for the current understanding of AI applications and for the identification of trends and future developments. It is expected that these fields of activity will undergo significant change in the coming years, driven by the ongoing AI transformation.

6.1.7 Characteristics of employees from dual partner organizations of the DHBW

A special focus of this study is on the "dual partners" of the DHBW. There are around 9,000 companies and social institutions throughout Germany that select their students themselves and send them to one of the DHBW university locations in Baden-Wuerttemberg for a dual course of study.

This group is particularly important for this study not only because of its relevance for the DHBW but also because these companies and organizations reflect the diversity of the Baden-Wuerttemberg and German economy - from small companies with 10 employees to medium-sized companies, large medium-sized companies and large international corporations such as SAP and Bosch with well over 100,000 employees. [7] What distinguishes this group from the other participants in the study?

Age distribution (employees with dual partners): What are the special features of the age distribution of the participants from the "dual partner" organizations of the DHBW (Baden-Wuerttemberg Cooperative State University) compared to the total of all participants? Figure 10 shows the respective numbers by age group:

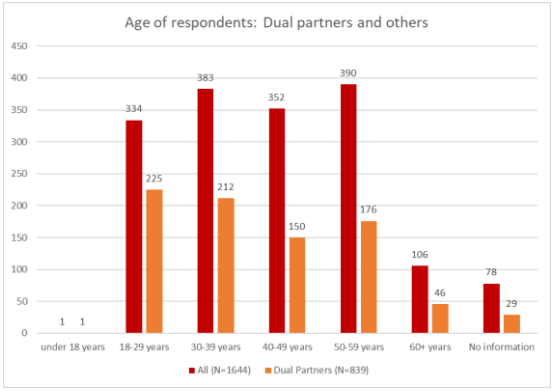


Figure 11 Comparison of age distribution among employees of dual partner organizations of the DHBW

Of a total of 1,644 participants, 839 came from dual partner organizations, i.e. just over half

[7] Exact figures on the more than 9000 dual organizations of the DHBW are not yet available. Our random sample provides an initial insightful look, but is not representative.

(51%). Here is a detailed interpretation by age group:

- Under 18 years of age: There is one person under the age of 18 in both the overall group and the dual partners, which indicates that very young participants tend to be the exception in this context.
- 18-29 years: There are a total of 334 participants in this age group, 225 of whom (67.4% of the age group) come from dual partner organizations. This shows that this age group is strongly represented in dual partner organizations, which could indicate a trend towards the recruitment of young adults or the integration of students into the professional world.
- 30-39 years: Of the 383 participants in this age group, 212 (55.3%) come from dual partner organizations. Here too, participation is significant, which indicates that people in this phase of life are actively involved in dual training.
- 40-49 years: Of the 352 participants in this age group, 150 (42.6%) are dual partners. The proportion falls in comparison to the younger age groups, which could indicate that this age group is less involved in dual training.
- 50-59 years: There are a total of 390 participants in this age group, of which 176 (45.1%) come from dual partner organizations. The proportion of participation is like that of the 40-49 age group.
- 60+ years: Of the 106 participants in the oldest age group surveyed, 46 (43.4%) are associated with dual partners. This could indicate a certain presence of older employees in further training measures or the involvement of experienced professionals.
- Not specified: 29 of the 78 participants who did not specify their age come from dual partner organizations. This corresponds to 37.2% of the group without age information.

In summary, the age distribution of the dual partners is comparatively younger, with the strongest representation in the 18-29 age group. This could indicate a strong participation of students or young employees in dual training programs. The proportion of participants from dual partner organizations tends to decrease with increasing age.

Gender ratio among employees of dual partner organizations: Figure 11 shows the gender distribution of respondents from DHBW "dual partner" companies and organizations compared to all respondents.

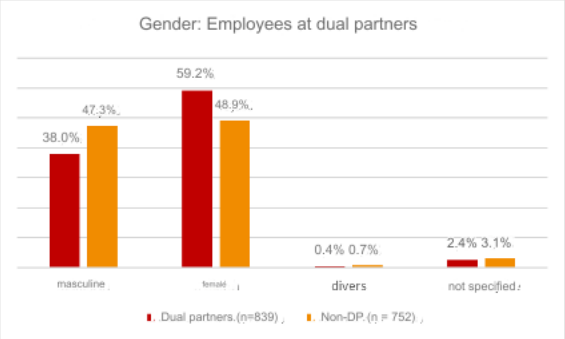


Figure 12 Comparison of the gender ratio among employees of dual partner organizations of the DHBW

Of a total of 1,644 respondents, 839 people (51.0%) came from dual partner organizations.

- Of the male respondents in total (704), 497 are employed by dual partners, corresponding to 59.2%. This means that the proportion of men is 9.3 percentage points higher than in the other organizations.
- The proportion of female respondents is correspondingly lower. Of 884 respondents who identify as female, 319 (38.0%) are employed by dual partners.
- From the "diverse" category (9 people in total), 3 (0.2% of the total) come from dual partner organizations.
- 47 people did not specify a gender. Of these, 20 people (1.2%) are employed by dual partners.
- The significantly lower proportion of female respondents at dual partner organizations could indicate specific sectors or occupational fields with a higher proportion of men, which are in any case particularly strongly represented among the employees who took part in our survey.

Organization size (employees of dual partner organizations):

- Figure 12 shows the distribution of respondents who are employed by dual partners of the DHBW according to the three categories of company size. Of the total of 1644 participants

- 15% (246 respondents) come from companies with more than 5000 employees,
- 50% (819 respondents) from large "Mittelstand" companies with 250 to 4999 employees,
- 30% (492 respondents) from micro-enterprises and small and medium-sized SMEs with up to 249 employees.
- 5% (87 respondents) did not specify the company size.

This means that almost exactly half of the participants come from larger SMEs. Small companies are represented by almost a third of respondents. Large companies with more than 5000 employees are the least well-represented.

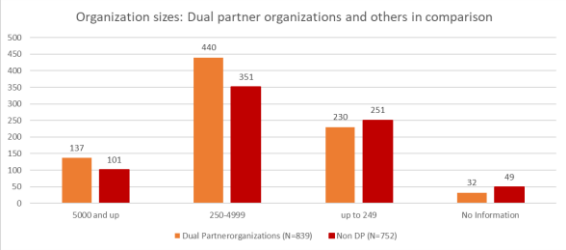


Figure 13 Organization sizes: Comparison of employees at dual partner organizations

Professional positions (employees of dual partner organizations):

Among all participants in the study who come from dual partner companies and organizations of the DHBW (839 people), the proportion of managers is strikingly high at 39.8% (334 of 839 people) - that is two-fifths (Figure 13). Among participants from other companies and organizations, the figure is 31.8% (239 of 752 people). This may be because an above-average number of managers were reached when the questionnaire was sent out and distributed via the DHBW channels.

In any case, it is important to keep in mind that a larger proportion of these people are involved in decisions in their organizations that also affect AI applications. Nevertheless, with three-fifths of employees at dual partners, there are enough people without a managerial position to also capture their perspective on AI skills and use.

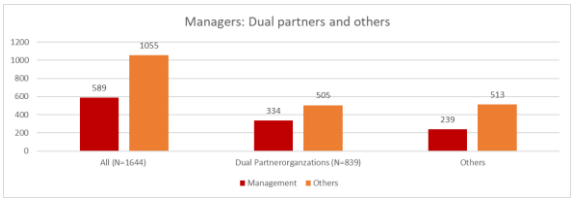


Figure 14 Proportion of managers among respondents who are employed in dual partner organizations

6.1.8 Representativeness of the sample

The random sample of the AIComp study on AI skills shows a remarkable congruence with the demographic characteristics of employees in Baden-Wuerttemberg.[8] Although the sample cannot be regarded as representative in the classical statistical sense, it largely reflects the gender proportion and, to a large extent, the age structure. This makes the AI-related results of the AIComp survey meaningful for the working population in Baden-Wuerttemberg as a whole, at least in these respects.

In other respects, one must differentiate precisely if one wishes to derive more far-reaching statements from the study. For example, occupations and activities in the fields of technology, organization, and education/training are over-represented in relation to the overall economy of Baden-Wuerttemberg. This distortion certainly has to do with the accessibility of different target groups through the DHBW study, but it could also be related to the fact that the willingness of individuals to participate in an AI study also reflects the asynchronicity of AI development in specific sectors and professions.

DHBW subject areas such as social work and health/nursing may be under-represented in the sample, as well as other socio-statistical

[8] See the microcensus figures published online by the State Statistical Office (Statistisches Landesamt Baden-Wuerttemberg 2021).

groups that may have a lower affinity for AI technologies. It can be assumed that the results primarily reflect the AI-related competences of those occupational fields that have already entered an early phase of AI transformation.
The results of the AIComp study thus offer valuable insights into the spread of AI skills within certain occupational groups in Baden-Wuerttemberg, about which nothing was previously known, at an important point in the development: In June/July 2023, the first effects of the major new wave of generative AI had just reached companies, but it was still too early for corresponding changes within organizations. There is, therefore, a need for further research in two respects: extrapolating the results to the entire working population is only possible with reservations due to the distortions mentioned above. At the same time, the object is a "moving target" in the highly dynamic transformation process: experiences, perceptions of one's sovereignty, and assessments of the future significance of the fields of competence will change constantly. The AI-Comp study offers a solid starting point for targeted further research to gain a comprehensive picture of AI skills development across the entire working population.

6.2 Use of artificial intelligence

Our random sample shows that the level of AI usage among participants in the study was already surprisingly high in June 2023. A total of 1397 participants (85%) use AI applications, and 247 participants (15%) do not use them. In the following sections, the degree of use, measured using the AI activity index, is examined for the most important subgroups.

6.2.1 AI usage by age group

Figure 14 presents a comparison of data on the use of AI applications broken down by age group:

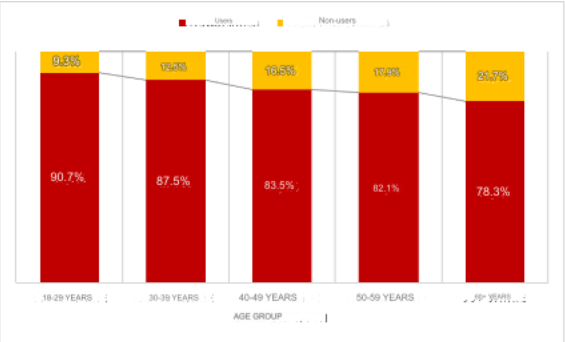


Figure 15 Users and non-users of AI by age group

The detailed breakdown by age group shows the following trends:

- In the 18 to 29 age group, 303 out of 334 people use AI applications. Only 31 people (approx. 9.3%) do not yet use any AI applications. (The only participant from the youngest age group under 18 is also a user).
- Among 30 to 39-year-olds, 335 out of 383 respondents use AI applications. The rate of non-users is around 12.5%.
- The 40 to 49 age group shows a slight increase in the proportion of non-users (approx. 16.5%): 294 out of 352 respondents use AI applications here, and 58 do not use them.
- In the 50 to 59 age group, the rate of non-users is higher again (17.9%): 320 out of 390 respondents use AI applications, and 70 respondents do not use them.
- The non-use rate is highest among the over-60s at 21.7%: 83 out of 106 use AI applications, 23 do not use them.
- 78 respondents did not specify their age. Of these, 61 use AI applications and 17 do not.
- The data shows a correlation between increasing age and the rate of non-use of AI applications. In the oldest age group, there are more than twice as many participants as in the youngest age group who do not use AI applications at all.

6.2.2 AI usage by gender

Of the 1644 respondents in the study, 704 identified themselves as female, 884 as male, and 9 as diverse. 47 people did not specify their gender. The following chart (Figure 15) shows the

percentage of users and non-users of AI applications by gender.

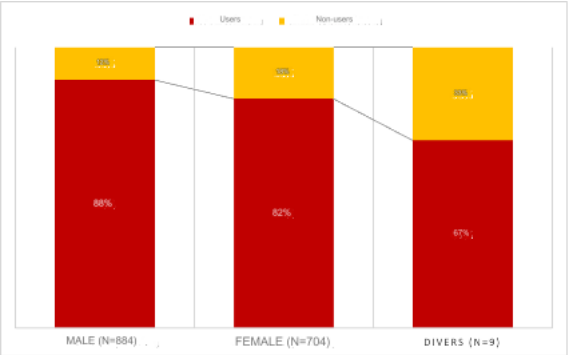


Figure 16 Users and non-users of AI by gender (all respondents)

- Of the 704 female participants, 574 are users and 130 are non-users. This means that around 18.5% of female participants state that they do not use AI applications.
- Of the 884 male participants, 780 use AI applications, and 104 do not, resulting in a non-user share of around 11.8%.
- Of the 9 participants who identify as diverse, 6 are users and 3 are non-users (33.3%).
- Among the participants who did not specify their gender, 37 are users and 10 are non-users.

The proportion of non-users among female participants is almost 7% higher than among male participants. It is not possible to say to what extent this is due to a different degree of acceptance and to what extent it is due to the conditions in the workplace.
(The absolute number of diverse participants is so small that the exact quotas are not statistically meaningful. The total number and the proportion of those who did not specify their gender is also so low that it has hardly any influence on the overall assessment).

6.2.3 AI usage by organization size

The data visualized in Figure 16 provides information on the use or non-use of AI applications in relation to the size of the organizations in which the respondents work.

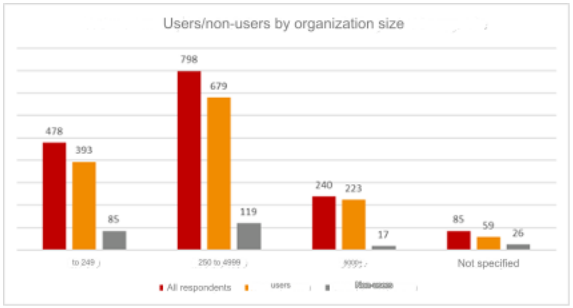


Figure 17 Users and non-users of AI by organization size (N=1644)

If the category "small and medium-sized enterprises" (SMEs) is further differentiated, the following picture emerges:

- In organizations with up to 9 employees, 33 respondents use AI applications, while 5 stated that they do not use AI applications. This corresponds to a non-user rate of approx. 15.2%.
- In organizations with 10 to 49 employees, 80 out of 104 respondents use AI applications. 20 respondents from this size category do not use AI applications, which corresponds to a rate of around 19.2%.
- In the category of 50 to 249 employees, 285 out of 355 respondents are users of AI, while 60 are non-users. This results in a non-user rate of approx. 16.9%.
- In larger organizations with 250 to 4999 employees, 679 out of 819 respondents use AI applications and 119 stated that they do not use AI applications. This is a non-user rate of approx. 14.5%.
- Among the very large organizations with 5000+ employees, 223 out of 246 respondents use AI applications, and 17 are non-users. This corresponds to a non-user rate of around 6.9%.
- 87 respondents did not specify the size of their organization. Of these, 59 use AI applications and 26 do not, which corresponds to a non-user rate of approx. 29.9%.

Especially in very large organizations with over 5000 employees, the proportion of non-users is significantly lower compared to smaller organizations. This could indicate a better availability of resources, a higher likelihood of implementing AI technologies, or a stronger promotion of digital transformation in larger organizations.

6.2.4 AI use by group: Dual partners, managers, and university lecturers

The available data provides information on the use of artificial intelligence (AI) by various target groups.

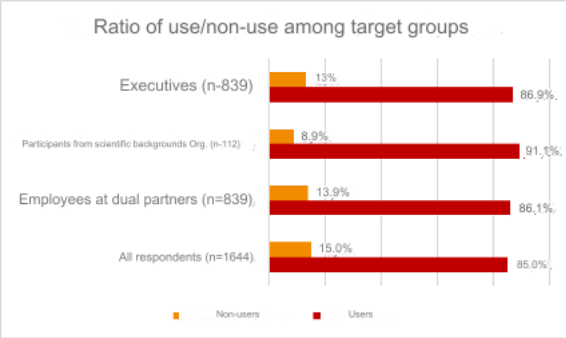


Figure 18 Ratio of AI users to AI non-users at dual partner organizations

Dual partner organizations: Figure 18 provides a closer look at the 839 employees at "dual partners" of the DHBW. Of these, 722 people (86.1%) already use AI, while only 117 people (13.9%) state that they do not use AI. This is slightly higher than the usage rate among the 752 participants from other organizations - here there are 635 (84.4%) users and 117 (15.6%) non-users.

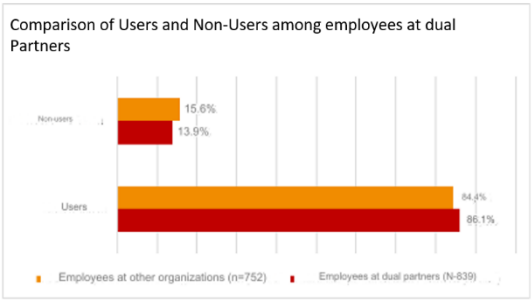


Figure 19 Use of AI by employees of dual partner organizations of the DHBW

Use of AI by teachers (Figure 19):

- University lecturers: Of 81 university lecturers surveyed, 71 (87.7%) use AI. Only ten people (12.3%) do not use it.
- If lecturers are considered together with all academic employees in universities and research organizations, the highest usage rate of all subgroups is obtained: Here, 102 out of 112 (91.1%) people use AI applications, and only ten people (8.9%) do not use them. (The non-users in this group are therefore all teachers).
- Non-teachers: Of the total of 1,532 participants who do not teach, 1,295 (84.5%) use AI applications, 237 (15.5%) do not.

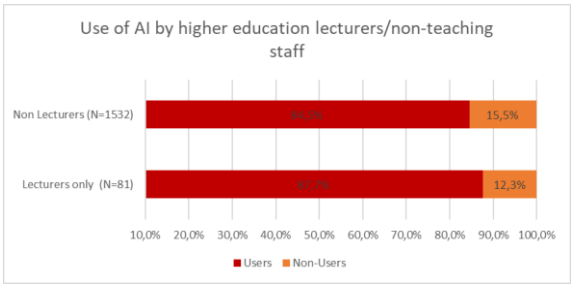


Figure 20 Use of AI by university lecturers in relation to all participants who do not teach

Use of AI by managers (Figure 20):

- Management: Von 589 Managers use 512 (86.9%) AI, while 77 (13%) do not use AI.
- Other roles: Of the remaining 1,055 participants, 885 (83.9%) use AI, and 170 (16%) do not use it.

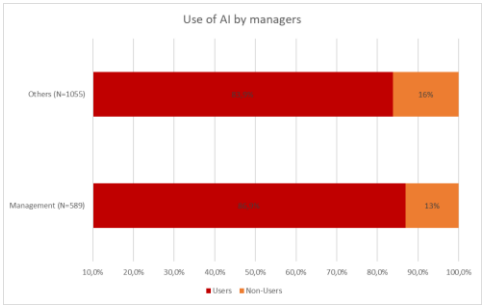


Figure 21 Use of AI by managers

The data shows that AI already has a high penetration rate among the employees of the DHBW's dual partners, with a high usage rate of 86.1% (Figure 18). Companies and organizations that work closely with the DHBW may have a stronger affinity for modern technologies such as AI and/or are better equipped to use these technologies due to their cooperation with the DHBW.

Interestingly, employees from universities and research institutions have the highest AI usage rate among the subgroups (91.1%). When looking at university lecturers alone, the figure is still 87.7%. It appears that the awareness and willingness to use AI among employees here is particularly fast ahead of AI integration by the institutions. Managers also show a high usage rate of AI at 86.9% - an indication that managers and decision-makers have also recognized

the importance of AI as a tool and as a technology to a particularly high degree.
In summary, it can be said that AI usage across all different groups was already surprisingly high in the summer of 2023: an indication of the disruptive dynamics of the development.

6.2.5 Type, degree, and frequency of AI use

Some further questions were asked about details of AI use: To what extent has the AI transformation already arrived in the respondents' professional lives? And if AI applications are already being used - in what way and with what degree of intensity is this happening, professionally and/or privately?

Type of AI use: Our data also shows how the 1644 participants in the study use artificial intelligence (AI) (see Figure 21). In the questions, we differentiated between passive use, active use, co-creation, and no use. Passive Use:

- 736 participants, which corresponds to 44.8% of the total sample, use AI applications passively. This could mean that these people use AI systems without being directly involved in their development or management. Examples of this could be the use of AI-based recommendation systems or personal digital assistants.
- Active use: 482 participants or 29.3% of the sample are active users of AI. This group could include people who not only use AI applications but are also involved in configuring or operating them. This could include developers, data analysts, or tech-savvy users who use AI tools for specific tasks.
- Co-design: 185 participants, corresponding to 11.3% of respondents, are involved in the co-design of AI. These could be, for example, experts who work on the development of AI models or users who actively provide feedback that is used to improve AI systems.
- No use: 241 people, or 14.7% of the total number of respondents, do not use AI applications. This could be due to a variety of factors, such as a lack of interest, lack of knowledge about AI, barriers to entry, or a conscious decision to avoid AI.

Most participants already use AI in some form, with passive use of predefined tools being the most common. AI applications now appear to be widespread and integrated into many everyday technologies. High scores for active use and co-creation, on the other hand, indicate that a significant proportion of respondents are already technically adept and may work in areas directly related to AI. The relatively high number of people who do not use AI should be the subject of further research to better understand the exact reasons and link them to suitable educational or awareness-raising measures.

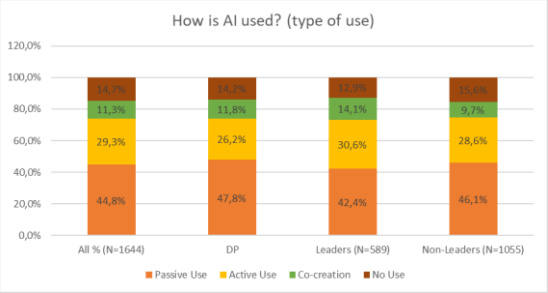


Figure 22 Type of use of AI by different target groups
** Question: How would you rate your use of AI applications? Four answer options, e.g. Active use: I understand the basic functioning of AI systems and actively use them in my everyday work.*

AI usage by organizational size: The chart below (Figure 22) shows the type of Artificial Intelligence (AI) usage broken down by organization size. The data represents the responses of 1644 respondents, divided into three categories of organizations: Large companies and organizations (246 respondents), larger "mid-sized" companies and organizations (819 respondents), and small and medium-sized enterprises (SMEs) and organizations (429 respondents). The types of use are categorized as passive use, active use, co-creation, and no use.

- **Several insights can be gleaned from the chart:** Passive use: The proportion of passive use is 42.33% for large companies, 46.0% for larger "medium-sized" organizations, and 45.1% for small companies. This shows that passive use is slightly more common in smaller companies than in large companies.
- Active use: There is an opposing trend here. In large companies, the proportion of active use is 31.3%, in larger "medium-sized" organizations 29.4% and in small companies

29.4%. Active use is therefore more prevalent in large companies.

- Co-design: Participation in the co-design of AI is highest in large companies at 18.3%, followed by larger "Mittelstand" organizations at 10.3% and small companies at 9.6%. This suggests that large companies may have more resources and skills to actively participate in the development of AI.
- No use: The proportion of respondents who do not use AI is lowest in large companies at 8.1%. In larger "Mittelstand" organizations, this proportion is 14.3%, and in SMEs 15.9%. This could indicate that AI is already further integrated into processes in large companies, while there is still potential for development in small companies.

Overall, we saw AI use in larger organizations tends more toward active participation and co-creation, which suggests a deeper integration of AI into company processes. In smaller companies, on the other hand, AI does not yet appear to be used as extensively, which is reflected in higher proportions of passive use and non-use. The results could be relevant for decision-makers in companies as well as for politics and educational institutions to develop targeted measures to promote AI competence and adoption in different company sizes.

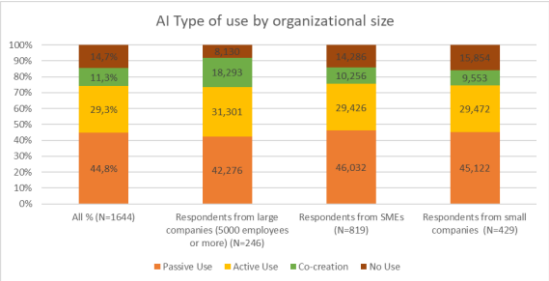


Figure 23 AI usage type by organization size

**Question: How would you rate your use of AI applications? Four answer options, e.g. Active use: I understand the basic functioning of AI systems and use them actively in my daily work.*

- **Frequency of AI use:** In the graphical representation of the frequency of AI use by organization size (Figure 23), the respondents are classified according to the frequency of AI use. The organizations of the 1644 respondents were divided into three categories: Large companies (5000 employees/MA or more), large medium-sized companies (250 - 4999 MA), and small and medium-sized enterprises (SMEs, up to 249 MA).

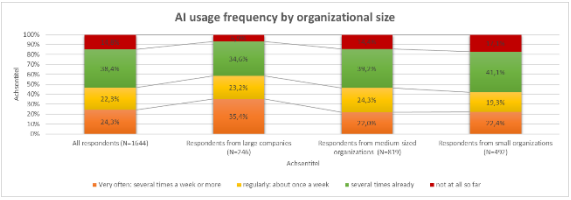


Figure 24 AI usage frequency by organization size

** Question: How often do you use AI applications? Choice: a few times already; regularly: about once a week; very often: several times a week or more; not at all so far.*

The overall sample (n=1644) shows the following frequencies of use:

- 24.3% of respondents use AI very frequently,
- 22.3% use AI regularly,
- 38.4% have only used AI a few times,
- 14.8% have not yet used AI.

The following picture emerges according to organizational size:
For large companies (n=246):

- A substantial 35.4% of respondents report very frequent use,
- 23.2% state that they use AI regularly,
- 34.6% have used AI a few times,
- a marginal proportion of 6.9% have not used AI to date.

In medium-sized companies (n=819):

- 22% of respondents use AI very frequently,
- 24.3% regularly,
- 39.2% a few times,
- 14.4% have not yet used AI.

In small companies (n=492):

- 22.4% use AI very frequently,
- 19.3% regularly,
- 41.1% a few times,
- 17.1% have not yet used AI.

The data shows that the frequency of use of AI is generally higher in larger organizations. In large companies, the proportion of respondents stating that they use AI very frequently is higher compared to smaller companies. This could be due to more extensive resources and a greater capacity to integrate new technologies in large companies.

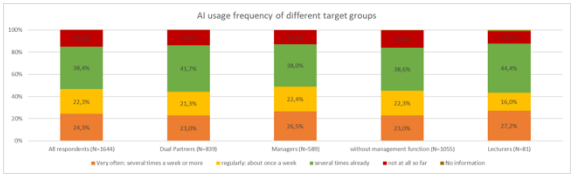


Figure 25 Frequency of AI use among different target groups

** Question: How often do you use AI applications? Choice: a few times already; regularly: about once a week; very often: several times a week or more; not at all so far.*

Looking at all respondents (n=1644), 14.8% use AI very frequently, while 38.4% use AI regularly. A proportion of 22.3% have already used AI a few times, and 24.3% of respondents have not yet had any experience with AI.

Among the dual partners (n=839), regular use is slightly higher than the average for all respondents at 41.7%, and very frequent use is 13.8%. This could indicate a more intensive integration of AI in the practice of this group.

Managers (n=589) show similar tendencies to the dual partners with a regular use of 38% and a very frequent use of 13.1%. This suggests that managers are active in the use of AI technologies, which is to be expected given their responsibility for the introduction and management of such technologies within organizations.

In contrast, people without a leadership role (n=1055) use AI slightly less regularly (38.6%) and less frequently (15.8%). This may indicate that AI is less integrated into their daily tasks or that they have less direct access to such technologies.

The higher proportion of very frequent use of AI among university lecturers (n=81) is striking, at 11.1%. In addition, the proportion of those who use AI regularly is the highest compared to the other groups at 44.4%. This could reflect the strong integration of AI in research and teaching at universities.

Overall, the data shows a clear tendency: the more responsibility and commitment a group has in relation to their professional role, the higher the frequency of use of AI appears to be. University lecturers and managers, especially, are more active users of AI. A more active approach to AI technologies can be observed among university lecturers and managers in particular, which suggests a greater affinity for new technologies in these professional groups. These findings could be important for the development of target group-specific education and training programs in the field of AI.

Context of use: An overall view of all respondents (n=1644) shows that the majority use AI in both their professional and private lives, with a share of 68.6% (see Figure 25). Purely professional use is also strongly represented at 65.2%. The exclusively private use of AI is lower at 19.2%, and a combination of professional and private use is remarkably high at 49.5%. These figures indicate that AI plays a role in many aspects of daily life and that the penetration of AI technologies in the private sector is considerable.

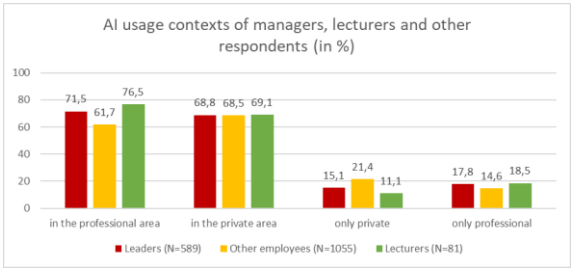


Figure 26 Comparison of AI usage context for different target groups

**Question: Do you use AI applications in your professional and/or private life? (Multiple answers possible.) Answer options: in the professional field; in the private field; neither.*

The target groups show that managers use AI more frequently in a professional context (76.5%), which reflects their role in the introduction and management of AI in companies. In contrast, the use of AI in the private sphere is higher among university lecturers (68.8%), which could indicate the application of AI in research and teaching.

Figure 26 shows a breakdown of the use of AI applications among 1644 respondents, divided into two groups: Dual partner respondents (839 respondents) and other respondents (805 respondents). Of the total number of respondents (N=1644):

- 65.2% (1072 people) use AI applications at work. This proportion is slightly lower among respondents with dual partners (62.9%), while it is higher among other respondents (68.5%).
- 68.6% (1128 people) use AI applications in the private sphere. Here too, the proportion is higher among respondents with dual partners (70.9%) than among other respondents (66.5%).

- 19.2% (315 people) use AI applications exclusively in their private lives, with a higher proportion of respondents with dual partners (21.9%) compared to other respondents (15.8%).
- 15.8% (259 people) use AI applications exclusively for work. The proportion of other respondents (17.8%) is higher than that of respondents with dual partners (13.9%).
- 15.5% (254 people) do not use AI applications either professionally or privately, although the proportions are similar in both groups (dual partners: 14.9%, other respondents: 15.6%).
- Almost half of the total, 49.5% (813 people), use AI in both their professional and private lives. The proportions are very similar in both groups (dual partners: 49.0%, other respondents: 50.7%).
- A very small number, 0.2% (3 people), stated that they did not use AI applications either professionally or privately or did not specify.

In summary, it can be stated that most respondents use AI applications, whether in a professional or private context, with a significant number also stating that they use AI in both areas. The proportion of those who use AI applications exclusively in their private lives is higher among respondents with dual partners, while the proportion of those who use AI applications exclusively for work is higher among the other respondents. The group of non-users of AI applications is small overall. These results show the increasing penetration of AI technologies in various areas of daily life.

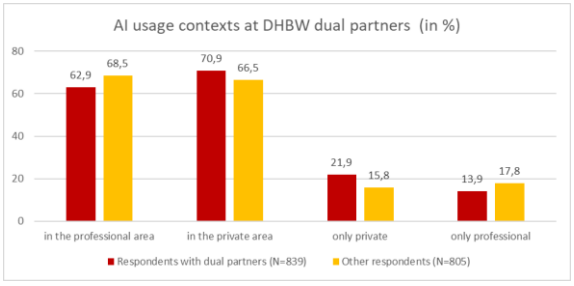


Figure 27 AI usage context among employees of dual partner organizations of the DHBW in comparison
**Question: Do you use AI applications in your professional and/or private life? (Multiple answers possible.) Answer options: in the professional area; in the private area; neither.*

Interestingly, the age groups show different usage patterns (see Figure 27). While the combination of professional and private use of AI is highest among 18- to 29-year-olds at 70.5%, this combined use decreases in the older age groups. Among the over-50s, the exclusively professional use rises to 72.2%, which indicates that older employees mainly use AI in a professional environment.

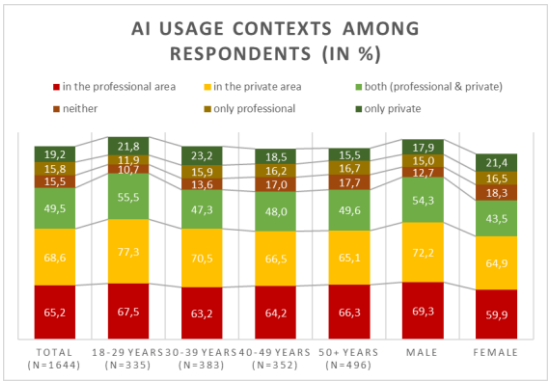


Figure 28 AI usage context by age group
**Question: Do you use AI applications in your professional and/or private life? (Multiple answers possible.) Answer options: in the professional field; in the private field; neither.*

Looking at the size of the organization, the professional use of AI is highest in large companies (71.5%), while in small companies (up to 249 employees) the purely private use of AI is most prevalent at 19.5% (see Fig. 28). This suggests that larger organizations may be quicker to adapt and integrate AI technologies into their processes than smaller companies.

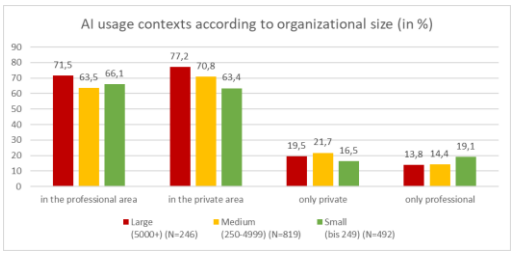


Figure 29 AI usage by organization size

In conclusion, the use of AI is widespread across all areas, with significant differences in use depending on gender, age and organizational size. These findings could be relevant for future strategies for integrating AI into professional and educational contexts, particularly regarding targeted training and further education programs.

6.3 Concept and empirics of the AI activity index

The development of the AI Activity Index (AIX) represents an innovative approach to evaluating the use of and commitment to artificial intelligence (AI). This scientific introduction outlines the methodological framework and the statistical derivation that led to the creation of the AIX and examines its application in a comprehensive study.

The basis of the AI activity index is the combination of two central variables: the intensity of use and the type of use of AI. The intensity of use is measured by the frequency of AI use, operationalized by the possible answers "a few times", "regularly about once a week" or "several times a week or more". The type of use distinguishes between passive, active, and formative use of AI technologies.

By scoring both variables (see 6.3.1), six levels of AI engagement are created, ranging from non-use to high-intensity use and formative use:

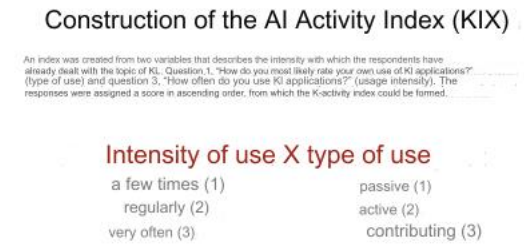


Figure 30 Construction of the AI activity index (AIX) from data on usage intensity and usage type

The six levels were then summarized into three AIX levels of activity according to the following matrix (see Figure 30). (The fourth level is the non-users).

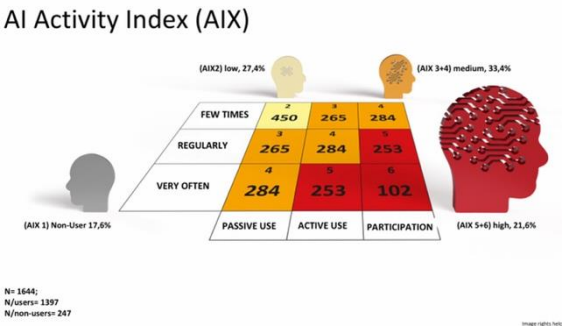


Figure 31 Construction of the AI activity index (AIX): matrix and division into levels

The application of the AIX enables a differentiated analysis of AI usage in different sub-samples and subgroups. This reveals relevant differences in the use of AI according to gender, age, organizational size, and professional background, which are explained in more detail below. The differentiated recording of the intensity and type of use illustrates the spectrum that exists in terms of commitment and attitude toward AI technologies. The introduction of the AI activity index thus proves to be a valuable tool for assessing and understanding AI usage in all subgroups. Such findings are not only important for scientific research but also for decision-makers in companies, organizations, and educational institutions who want to develop the AI skills of their employees in a targeted manner.

6.3.1 Statistical construction of the AI activity index

In the following, we explain in detail how the AI Activity Index (AIX) was statistically constructed. The formation of the composite index value is based on answers to two key questions: the frequency of AI use (Q1) and the type of AI use (Q3). Based on the responses, scores were awarded for the answers to the two questions:

- There were three possible answers for the type of use (Q1), which were rated as follows: "passive" (1 point), "active" (2 points), "co-creation" (3 points).
- There were also three levels for the frequency of use (Q3): "a few times" (1 point), "regularly" (2 points), and "very often" (3 points).

Non-users were given a score of 0. Six possible levels of AI activity were created by adding the scores from these two questions. To improve the informative value, these levels were further summarized. This resulted in a four-level classification (Figure 30 and Figure 31): high AIX (5+6), medium AIX (3+4), low AIX (2) and no activity (0).

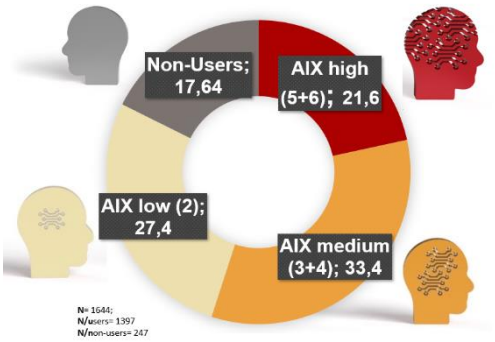


Figure 32 Distribution of the AI activity index (all respondents)

This index was then used to analyze AI activity in different demographic and organizational groups. Significant differences and trends emerged within the groups surveyed, for example across characteristics such as gender, age, and company size, but also concerning subgroups such as managers and employees without a management function or researchers and teachers.

Figure 31 shows how the overall sample is distributed across the groups:

- AI activity index high: This group comprises 355 respondents, which corresponds to 21.6% of the total sample (N=1644). People in this category use AI intensively and are likely to have a high level of competence in AI technologies and applications.
- AI activity index medium: 549 people are categorized here, representing 33.4% of the total number of respondents. This group uses AI to a medium extent, which could indicate a moderate familiarity and integration of AI in their areas of activity.
- AI activity index low: With 450 people, corresponding to 27.4% of the total, this category indicates that AI is either only used to a very limited extent or its use is not fully integrated into processes.
- Non-users: This group consists of 247 respondents, which makes up 15.0% of the total sample. These people do not use AI at all, which could be attributed to a variety of factors, such as a lack of resources, skills, or a lack of necessity in the context of their work.
- Rest = users without an AI activity index: 43 people, or 2.6% of respondents, fall into a special category known as "rest". This appears to include users who, according to another question (Q3), use AI but have not been assigned an AI activity index due to an implausible combination of answers from question 1 and question 3.

In summary, the distribution shows that a significant proportion of respondents in the sample use AI to varying degrees, with a slight preponderance among those with a medium AI activity index. However, a significant proportion of respondents do not use AI, indicating potential areas where AI skills and use could still be developed.

The analysis of the study data enabled the development of an AI Activity Index (AIX), which combines the intensity and type of use of artificial intelligence in a consolidated measure. This index was successfully applied to all participants in the study. The AIX proved to be a significant predictor of the respondents' assessments of competence and showed a significantly higher explanatory power for these assessments than traditional demographic variables such as age and gender.

6.3.2 AI activity index concerning relevant groups

The Artificial Intelligence Activity Index (AIX) can now be set in relation to all sub-samples and sub-groups. In Figure 32 and Figure 33, the AIX is broken down into different age and gender categories:

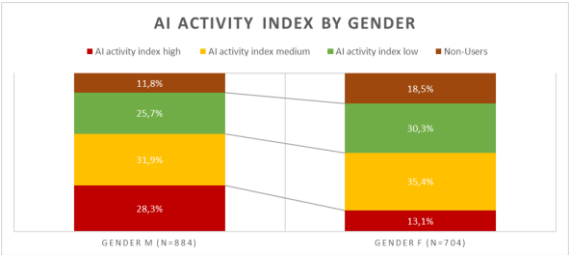


Figure 33 AI activity index by gender

AIX and gender:

- It is noticeable that there is a higher tendency towards a high KI activity index among men (28.3%) than among women (13.1%).
- However, the proportion of men with a medium AIX is slightly lower than that of women (minus 3.4 percentage points).
- The percentage of non-users is again significantly higher for women (18.5%) than for men (11.8%).
-

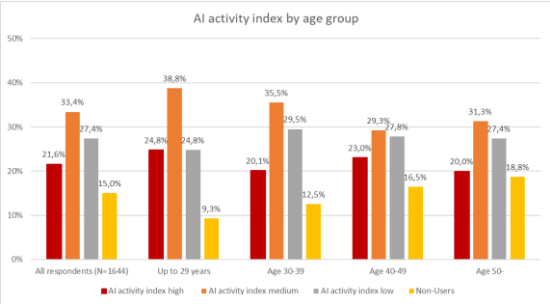


Figure 34 AI activity index by age group

Concerning the AIX of age, the results are as follows:

- The KI activity index is highest both at the top (24.8% here) and in the middle category among younger respondents up to the age of 29 (24.8%).
- In the middle age categories (30-39 and 40-49), the spread of AIX values is less pronounced. The 40-49-year-olds have higher AIX values at the top than the 30-39-year-olds, who are ahead in the middle range. This could be due to the management hierarchies.
- Among the over-50s, the percentage of people with a high KI activity index drops to 20%. The percentage of the group with a low AIX rises continuously across the age groups and is highest among older people, as is the percentage of non-users (18.8%).

It turns out that younger individuals and men show an increased tendency to use and engage with artificial intelligence, an observation that is consistent with the general perception, given the youthfulness and technical specialization of this technology. Nevertheless, scientific diligence demands that we refrain from premature generalizations. The reduced activity of older people in the field of AI can be attributed to a variety of causes, which are not exclusively due to a technology-related reluctance, but also to technological barriers, a lack of training opportunities, or divergent professional profiles.
Figure 34 below shows the AIX among respondents from different company sizes: Large companies (n=246), larger "Mittelstand" organizations (n=819), and small companies (n=492).

Respondents from large companies (over 5000 employees):

- 32.9% of respondents from large companies have the highest AIX value. This is the highest percentage of all subgroups - company size is therefore of particular importance here compared to other characteristics.
- Accordingly, the non-user rate (6.9%) is also the lowest among respondents from large companies - an indication that large companies may have built up more resources and a stronger infrastructure for the use of AI.

Respondents from larger "medium-sized" organizations (250 - 4999 employees):

- Most respondents with a medium level of AI activity come from larger "medium-sized" organizations (36.4%).
- There is also a significant number of non-users (14.5%), which may indicate a variance in the acceptance and implementation of AI in this category of organization.

Respondents from "small and medium-sized enterprises" (SMEs) and micro-enterprises:

- The proportion of non-users (17.3%) is highest among employees from small companies. Here, the "AI maturity level" is likely to have been inhibited by a lack of AI knowledge and limited resources, at least until the start of the big wave driven by "generative AI".
- However, this does not seem to apply to all small companies: The AIX score for high AI activity level is 20.5%, which is significantly lower than large companies, but comparable to larger "Mittelstand" organizations.

The empirical findings indicate that company size plays a significant role in the extent of AI use and the associated commitment. Large

companies in particular show an advanced integration of the systematic development of AI competences over the last decade. A positive correlation between company size and the AI activity index (AIX) values of employees can also be observed consecutively for larger SMEs as well as for smaller companies and organizations.

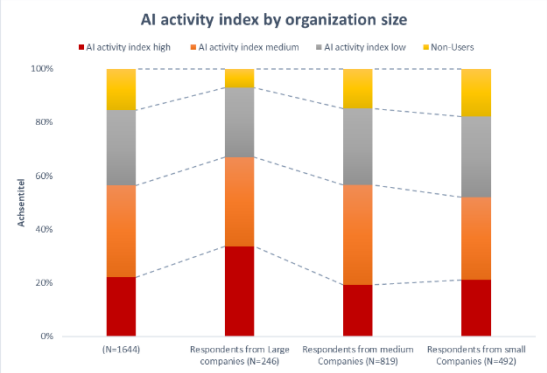


Figure 35 AI activity index by organization size

The dual partner organizations of the DHBW do not show any conspicuousness about the AI activity index but are on average. What is striking, however, is the deviation when looking at the subgroup of managers: Here, the proportion of employees with a high AIX is a quarter (25.3%). For those without a managerial position, it is only a fifth (19.5%). (see Figure 35)

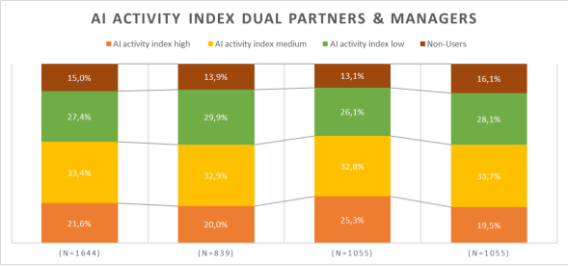


Figure 36 AI activity index among employees of dual partner organizations and managers

The following picture emerges concerning university members. The study examined three groups of university members: University lecturers (n=81), university staff of all kinds (n=112), and non-teaching staff (n=1532).

University lecturers (n=81):

- University teachers show a higher rate of high AI activity index at 27.2% compared to non-teachers (20.8%).
- At 25.9%, the percentage for the medium AI activity index is also lower than for non-teaching staff, where it is 33.7%.

University staff (all) (n=112):

- University staff shows a strong overall commitment to AI, with the highest percentage of high AI activity index (33.0%) among the three groups considered.
- The average AI activity level is 29.5%, which indicates a balanced level of AI usage.
- The lowest AI activity level and non-use are represented at 28.6% and 8.9% respectively, suggesting that the majority of this group shows at least some level of engagement with AI.

Non-teachers (n=1532):

- The non-teaching group shows a diverse picture with an even distribution across the different AI activity levels.
- The highest AI activity level is reached by 20.8%, while the mean AI activity index is 33.7%, which is the highest value among the three groups.
- The proportion of non-users is 15.5%. The value is higher compared to university employees and indicates that a significant proportion of this group does not use AI.

The results show that within the university community, university staff are the most active group concerning AI, followed by university lecturers (see Figure 36). This could indicate a greater involvement and use of AI-related resources in research and teaching. Non-teaching staff, on the other hand, show a wider range of AI usage levels, which could be attributed to different roles and tasks within higher education administration and services, where AI is used to varying degrees.

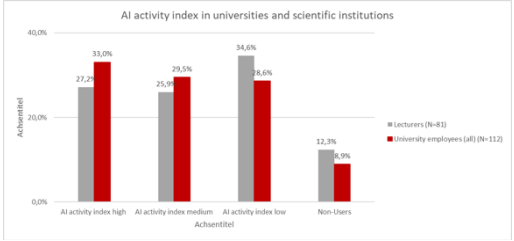


Figure 37 AI activity index in universities and scientific institutions

6.4 Attitudes of respondents towards AI: AI in the opinion mirror

The available data from the survey of 1644 respondents also provides information about attitudes and expectations regarding artificial intelligence (AI) in the work context and its potential influence on personal areas of life.

6.4.1 Assessment of AI among all respondents

The AIComp study is about the Future Skills of individuals, i.e. not just about their role as employees of companies or as professional representatives (see Figure 37). Personal attitudes play an important role here. Five questions addressed the fundamental evaluations and assessments of AI in the living environment. Three of these questions relate to the personal area of work, and two others to fundamental assessments of AI.

Positive assessment of AI:

- A majority (73%) of respondents rate the use of AI in their area of work positively. This indicates a general acceptance and possibly a positive perception of efficiency increases and advantages of AI in the world of work.

Influence of AI on work tasks:

- The high level of agreement (87%) with the statement that AI will influence work tasks in the near future reflects an awareness of the rapid advancement of AI technologies and their impact on the labor market.

AI in personal life:

- Opinions are divided (38%) regarding the impact of AI on important decisions in personal life areas - a possible indication of the sensitivity of these areas and the mixed feelings towards greater data dependency and higher levels of automation.

AI and job loss:

- A significant number of respondents (58%) agree with the statement that AI will lead to job losses in the future. The concern that automation could replace human labor is also and especially fueled by AI.

The superiority of AI:

- As many as 38 percent of respondents believe that AI will eventually be superior to human intelligence. This certainly reflects the impact of the debate on the long-term effects of AI, including the development of superintelligence and its ethical implications, which was particularly intense at the time of the survey in June and July 2023.

The results of the survey of a diverse cross-section of employees in Baden- Württemberg show the resonance of public discourse and current theoretical considerations. In social science research on technology adoption, acceptance and trust in technologies are regarded as central determinants (cf. Venkatesh et al. 2003). The generally positive attitude evident in our survey corresponds to the assumptions of the Technology Acceptance Model (TAM). Reservations regarding the loss of jobs are paralleled by the theories of economic disruption and Schumpeter's concept of creative destruction, which have become more influential during digitalization. In addition, the perceived skepticism towards the influence of AI on individual decisions could reflect the prevailing data protection concerns and demands for stronger regulation in Germany. Given the major AI wave triggered by ChatGPT at the turn of 2022/23, the media is currently intensively discussing the controversy as to whether general artificial intelligence or even artificial superintelligence could harbor uncontrollable risks for humanity. Overall, the survey results reflect a complex spectrum of hopes and fears that are essential for understanding the social dynamics of technology acceptance and offer important implications for shaping political and educational strategy decisions in the digital age.

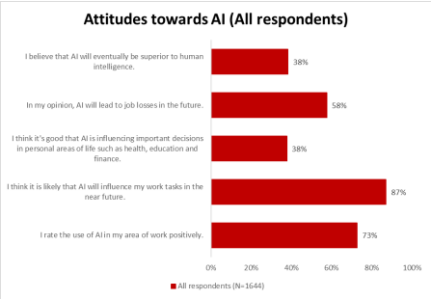


Figure 38 Attitudes towards AI among all respondents

6.4.2 Attitudes towards AI among different target groups

The available data reveals the attitudes of various target groups, including dual partners, other respondents, managers, university staff, and employees from large, medium-sized, and small companies (see Figure 38).

- What is striking is the positive assessment of the use of AI in the workplace, which is consistently high across all groups, with 73% among all respondents and similar percentages in the subgroups. Managers (78.4%) and university lecturers (78.6%) show the highest values, while respondents without a management function (69.4%) and from small companies (68.5%) show slightly lower, but still high approval rates.
- The assumption that AI will influence work tasks in the near future is very strongly supported across all groups at over 85%. Even at this early stage, there seems to be a broad awareness of the imminent changes brought about by AI technologies.
- The influence of AI on important personal decisions is viewed positively by 38% of respondents overall, with only slight fluctuations between the groups. Skepticism therefore predominates here.
- Around 58% of respondents in almost all groups expect AI to lead to job losses in the future. This shows the uncertainty about the impact of AI automation on activities that still account for a large proportion of many occupational profiles.
- The assumption that AI will be superior to human intelligence varies only slightly between the groups and is relatively consistent at around 38%. However, the majority remain skeptical of far-reaching technological prophecies.

The first thing that catches the eye here is the commonalities: despite slight fluctuations in attitudes between the various subgroups, the data shows a surprisingly coherent perception of AI. It seems as if digitalization and the introduction of AI technologies in organizations evoke a similar understanding and similar expectations among employees - relatively independent of age, gender, company size, and professional activity.
Against the backdrop of existing knowledge on the penetration of digitalization in organizations, these results reflect a universal recognition of the importance of AI. The uniform views across company boundaries may indicate the general spread of AI-related discourse and the increasing presence of these technologies in daily working life. It turns out that regardless of the size or type of organization, AI is seen as a significant factor for future work design. This trend is consistent with theories predicting increasing technologization and automation across all sectors of the economy and highlights the need for an adaptable workforce that is ready to take on new technological challenges.

The following figure presents the attitudes towards artificial intelligence (AI) among employees from large companies (n=246), medium-sized companies (n=819), and small companies (n=492).

Evaluation of the use of AI:

- Employees from large companies rate the use of AI in their area of work most positively at 83.7%, which indicates a broader acceptance and possibly also greater exposure to AI technologies in such organizations.
- In medium-sized companies, this positive rating is 73.0%, while in small companies it drops to 68.5%. This decrease could be due to fewer resources and infrastructure for AI in smaller organizations.

Influence of AI on work tasks:

- The expectation that AI will influence work tasks in the near future is high in all three groups, with slight differences: 88.6% in medium-sized companies, 87.8% in small companies, and 86.1% in large companies. This indicates that, regardless of company size,

there is broad recognition of the importance of AI for the future of work.

Influence of AI on personal decisions:

- Employees from medium-sized companies (44.7%) and from large companies (41.1%) are more inclined to welcome the influence of AI on personal decisions than those from small companies (30.9%). This could be due to a greater familiarity with the positive applications of AI in larger organizations.

AI and job losses:

- The concern that AI could lead to job losses is relatively similar across all company sizes: 54.9% for large companies, 58.0% for medium-sized companies, and 58.1% for small companies. This widespread concern reflects general uncertainty about the long-term impact of automation on the labor market.

The superiority of AI over human intelligence:

- The belief that AI will eventually be superior to human intelligence is more prevalent in medium-sized companies (41.1%) and large companies (38.6%) than in small companies (34.8%). This could reflect the perception of technological progress and the future development possibilities of AI in larger organizations.

Similarities and differences:

- Similarities: In all three groups, the expectation that AI will influence the world of work is high. There is also a common awareness of the risk of job losses due to AI.
- Differences: Employees from large companies have a more positive attitude towards AI overall and are more likely to see their personal decisions influenced by AI than employees from small companies.

Against the backdrop of digitalization in organizations: The data reflects the widespread assumption that larger organizations have a more advanced digitalization, which is reflected in a higher acceptance and positive evaluation of AI. Medium-sized and especially small companies, on the other hand, still seem to be struggling with challenges in the integration of AI technologies, which is reflected in a lower agreement with the positive impact of AI on personal decisions and a lower positive overall assessment.

These differences could result from differences in the availability of resources, access to technology, and a differentiated corporate culture in terms of innovation and technology acceptance.

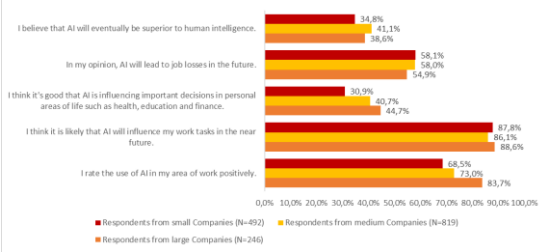


Figure 39 Attitudes towards AI by organization size of respondents

6.4.3 Attitude towards AI depending on AIX

It is interesting to look at these answers in relation to the KI activity index (see Figure 39). The answers are more or less clearly but consistently related to the AIX value:

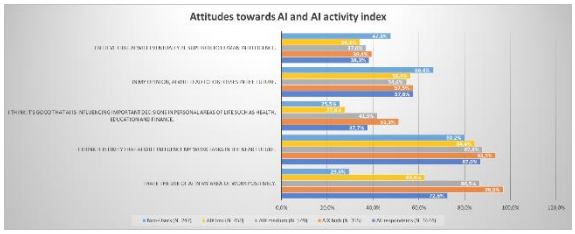


Figure 40 Attitudes towards AI by activity index

The data presented shows a clear correlation between the respondents' Artificial Intelligence Activity Index (AIX) and their attitude towards AI: people with a higher AIX tend to have more positive views on AI in various contexts.

Positive assessment of AI in the workplace:

- Among respondents with a high AIX, 96.9% rate the use of AI in their area of work positively. This proportion is significantly higher than in the other groups and indicates that a more active engagement with AI is associated with a more positive perception of its benefits.

Influence of AI on work tasks:

- Among those with high AIX, 93.5% believe that AI will influence their work tasks soon, compared to 80.2% of non-users. This trend underlines that people with a more intensive involvement with AI are more likely to recognize the future relevance of AI in their field of work.

AI and decisions in personal areas of life:

- More than half of people with a high AIX (51.3%) are in favor of the influence of AI on personal decisions, while only 25.5% of non-users share this view. This could indicate that a higher level of AI activity correlates with greater confidence in the positive role of AI in personal matters.

AI and job losses:

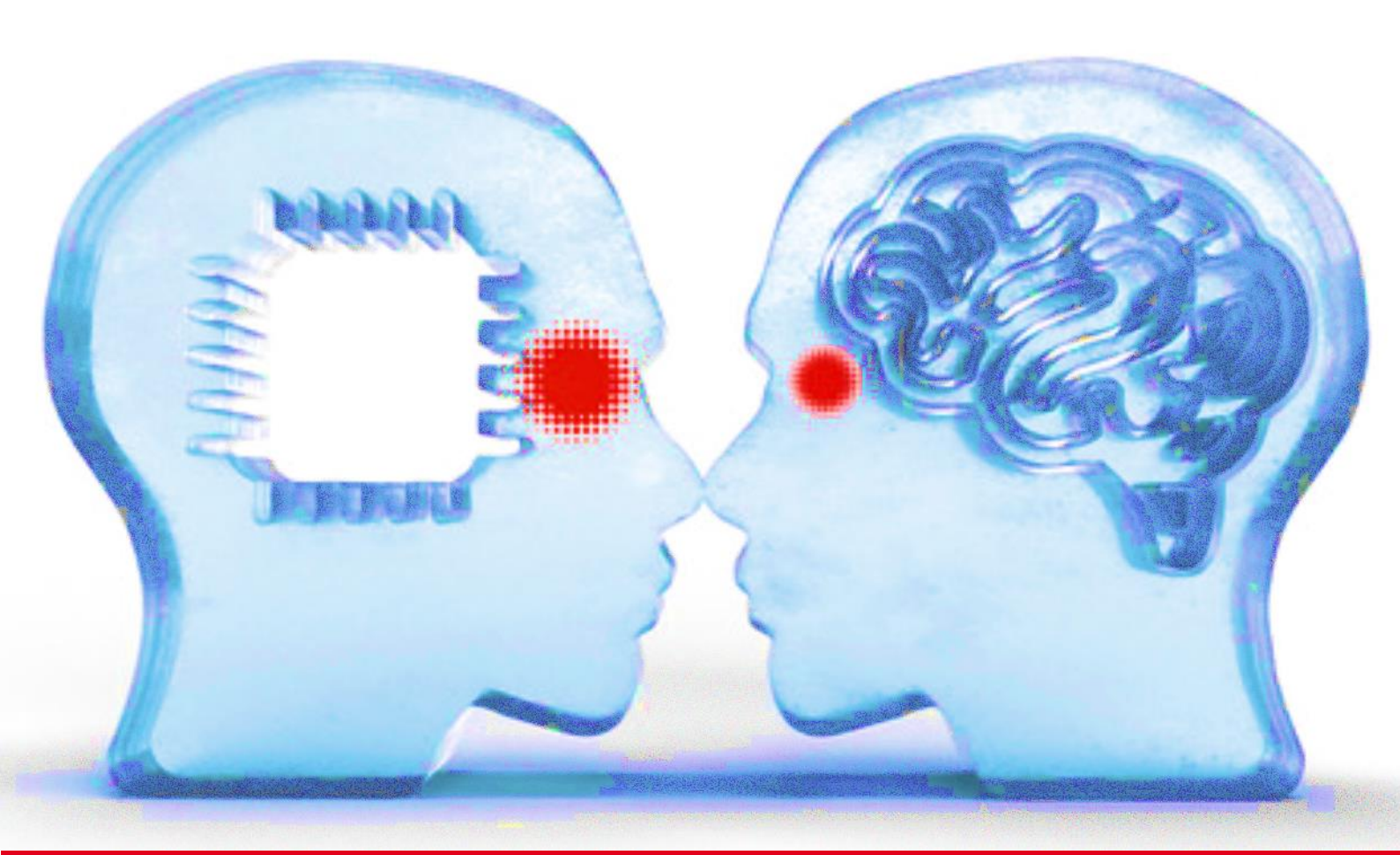
- Interestingly, concern about AI-induced job losses is highest among non-users (66.4%). This could be due to a certain distance or skepticism towards AI, possibly reinforced by a lack of familiarity or negative perceptions.

The superiority of AI over human intelligence:

- The belief in the future superiority of AI over human intelligence is strongest among non-users (47.8%), which seems para-dox, as this group also has the lowest level of positive evaluation of AI. This could indicate a certain ambivalence or even fear of the uncontrolled development of AI.

These data reflect a significant differentiation in attitudes towards AI based on individual experience and interaction with this technology. People who actively work with AI (high AIX) not only recognize the potential of AI but are also more optimistic about its positive impact on work and personal life.

In the context of the penetration of digitalization in organizations, these results reflect that people working in an AI-intensive environment tend to see AI as an asset rather than a threat. The results emphasize the need to promote AI skills and understanding in the workforce to fully exploit the benefits of AI technologies while reducing potential fears and misunderstandings.



7

7 Importance, experience and self-assessment concerning Future Skills

In a time of permanent transformation through networking, digitalization, and artificial intelligence (AI), the question of the ability to act in technology-centric contexts is becoming increasingly important. This AIComp study focuses on this key topic through a well-founded operationalization that distinguishes three important dimensions: the **experience** in dealing with AI, **the future significance** attributed to AI-related skills by the participants, and the self-assessment of their **sovereignty** concerning the 12 fields of skills.

Experiences directly reflect the practical engagement with AI technologies. This includes not only the use and understanding of AI systems but also the application of these technologies to solve specific problems.

The importance of the future is closely linked to the respondents' values and reflects the importance they attach to AI Future Skills.

Self-assessment or confidence captures the respondents' self-perception of their skills and knowledge of AI.

The breakdown into these three dimensions represents an innovative framework that allows us to take a closer look at the interplay between practical engagement with AI, personal values, and self-reflective competence assessment. The AIComp study thus not only offers new perspectives on individual and collective ways of developing skills but also valuable insights into the transformation process of a society that is preparing for a future characterized by technological change. This creates a holistic picture of the ability to act regarding AI Future Skills.

To further operationalize the three dimensions, three questions were constructed for each of the competence fields identified in the qualitative preliminary study:

- A question about previous experience with AI in this area,
- a question on your assessment of your sovereignty regarding the respective Future Skills
- and a question on the assessment of the future importance of the respective Future Skills for the professional future.

The questions were discursively validated by a team of researchers and checked for comprehensibility in several pretest rounds. They are listed in the appendix. For each question, there were four possible answers on a Likert scale: "Fully agree", "Rather agree", "Disagree" and "Strongly disagree". For the evaluation of the competence profiles shown below, the scale was dichotomized and the top two and bottom two scale points were combined and shown as a percentage. In the following diagrams for the three competence dimensions, the top two values are combined to form a "TOP2 value".

In the following, the three competence dimensions are first presented in context and compared with the 12 competence areas. Subsequently, conspicuous discrepancies between the competence dimensions in the individual fields are discussed, which allows conclusions to be drawn about particularly required competences. The conclusion about special competence needs is particularly obvious where the respective values for experience and sovereignty are conspicuously low or where there are discrepancies between the assessment of the future on the one hand and experience or the feeling of sovereignty on the other.

The questions in the study were based on the 12 areas of competence postulated in the first version of the Future Skills competence model. The evaluation of the study data was also intended to validate this model and modify it if necessary. For each area of competence, questions were asked about the three dimensions of competence, resulting in 36 questions:

- 12 questions on 4 competences for the technical-instrumental handling of AI (instrumental digital competence, critical digital competence, system design competence, creative design competence)

- 9 questions on 3 competences for the social use of AI (initiative competence, cooperation competence, communication competence)
- 15 questions on 5 competences for personal interaction with AI (decision-making competence, learning competence including further training, critical thinking, ethical competence, self-competence)

The answers provide differentiated data profiles with revealing patterns and a complex picture for each respondent and for the various subgroups - of the skills and competence requirements of people who are increasingly confronted with AI, but also of the respective conditions in the workplaces that are the daily environment for these people.

7.1 Experience as a competence dimension

A thorough analysis of AI-related Future Skills provides valuable insights into the current landscape of digital transformation in the world of work and life. The figures from the survey of respondents show the prevalence and level of digital skills needed to navigate an increasingly AI-driven environment. These skills reflect not only the ability to keep pace with technological change but also critical awareness, ethical considerations, and the ability to collaboratively problem-solve in a digital context. In the following interpretation, the different competences and related experiences of the interviewees are highlighted and discussed in relation to the wider theoretical and statistical field of social science and digitalization research.

The respondents have varying degrees of experience concerning AI Future Skills. For a clear presentation, the data was first dichotomized - i.e. the top two scale points and the bottom two scale points were added together. These were then presented as a percentage of the responses for the individual competence items in the following figures (n=1644 in each case):

- The high value for communication competence experience (84.1%) shows that most respondents are already actively participating in exchanges on AI topics - an indication of a high willingness to engage with these new technologies and share knowledge.
- System design competence: The high experience rate of 70% indicates a strong ability to conceptualize and understand AI systems in the context of their work.
- Critical digital competence: 69% of respondents state that they understand the logic behind AI systems. This is crucial for the use and control of AI tools and applications.
- Decision-making competence: 68.7% use AI recommendation systems in their field of activity, which indicates an integration of AI into the decision-making process.
- Instrumental digital competence: 62.3% of respondents use AI applications as a tool, which confirms the spread of AI tools in everyday working life.
- Critical thinking: An experience rate of 59.1% indicates a critical approach to AI-generated information.
- Initiative competence: The ability to make AI-based suggestions is reported by 43.7%, which shows proactive engagement with AI.
- Ethical competence: A value of 38.9% could mean that ethical considerations about AI are present but not consistently deepened.
- Creative design competence: 38.1% have experience with AI in creative processes, which indicates potential for innovative solutions.
- Learning competence: 35.8% have undergone further training on the topic of AI in the last 12 months, which indicates continuous further development in this area.
- Self-competence: 29.9% adapt AI-based systems to their needs.

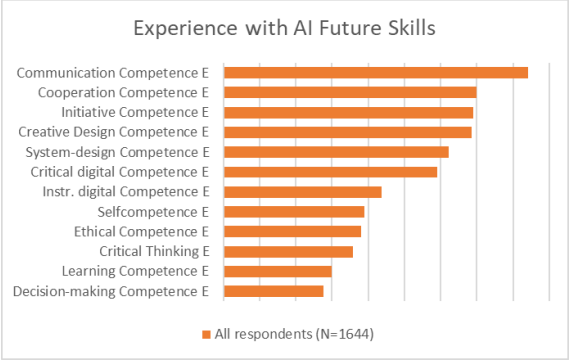


Figure 41 Experience with AI-related Future Skills (12 AIComp competence fields)

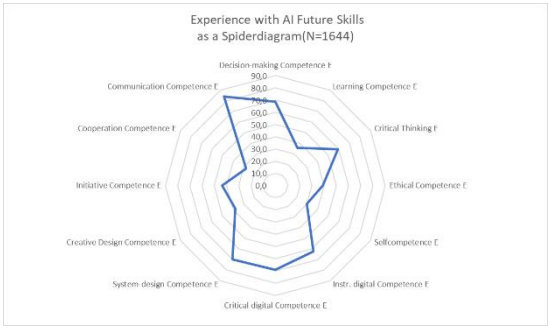


Figure 42 Experience with AI-related Future Skills (12 competence fields) as a spider diagram

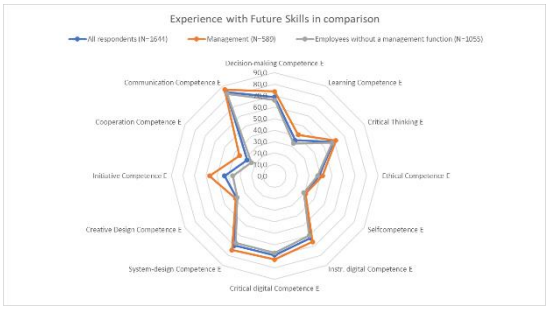


Figure 43 Experience with AI-related Future Skills (12 AIComp competence fields) with and without a management function

The chart and the associated data show that managers have higher scores in all the competence areas listed than employees without a management function. This indicates that managers have a broader range of competences in the context of AI or at least have a higher self-perception of these competences. Particularly noteworthy is the significant difference in the areas of initiative competence and cooperation competence, which underline the ability to take initiative and work together with AI technologies. However, critical digital skills, which measure the in-depth understanding of AI systems, show less pronounced differences between the groups, suggesting that a sound critical understanding of AI technologies is valued similarly across different professional levels. Communication competence, as one of the fundamental skills in the context of AI, shows the highest values among all respondents, which underlines its central role in the digital transformation.

The values for experience differed only slightly in terms of age and gender. A much more meaningful differentiation into subgroups is provided by the AI activity index, which was determined for the respondents. Figure 41 shows the profile differences in relation to the three AIX levels determined. The available data reflect how different the respondents' experience with AI skills is depending on their AI activity index (AIX).

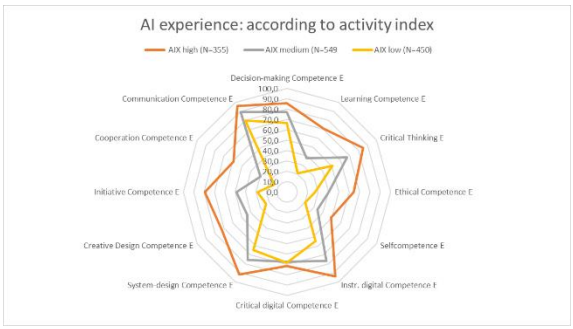


Figure 44 AI experience on the 12 competence fields in relation to the AI activity index

This diagram shows how the values for AI experience differ regarding the 12 competence fields depending on the AIX level. This follows the expected pattern: respondents with a high AIX value also have more experience in almost all competence fields, and this also varies accordingly for the medium and low AIX levels. Participants with a high AIX score (355 respondents) show a high level of decision-making competence (85.6%) and instrumental digital competence (93.8%). This reflects the active engagement with and use of AI. Non-users (247 respondents) consequently show significantly lower values here (decision-making competence 30.8% and instrumental digital competence 5.7%).

It is striking that the lower the AIX value, the lower the competence values. This is particularly evident in learning competence (from 70.7% for AIX high to 11.7% for non-users) and initiative competence (from 79.2% for AIX high to 13.0% for non-users). It remains to be seen to what extent this is due to a lack of opportunities and to what extent it is due to a lack of willingness to engage with AI and use it for their purposes.

However, it is striking that communication skills remain relatively high across all groups: Even those who have less practical experience

with AI seem to feel the need to engage with AI.[9]

- The situation is different in one area of competence: "critical digital competence", i.e. the ability to look through AI systems critically and analytically. At 68.5%, people with a low AIX value attribute more experience to themselves here than participants with a medium AIX, and almost as much as participants with a high AIX (71.5%).

- Which skills have the relatively highest values for experience across all AIX groups? In the first place are "communication skills" concerning AI topics. Even 65.2% of non-users ascribe this to themselves. This probably means that there is already a lot of talk about AI everywhere, relatively independent of how intensively it is used. The fact that "system design competence" has consistently high experience values can be explained by the specific question: "I have already imagined how I could use AI systems for my field of activity in the future." So, it is not so much the practical experience with the concrete design of AI systems that is important here, but rather the experience of thinking about it. This also shows the high level of attention paid to AI by the respondents.

- Experience with AI training was asked about in connection with "learning competence". In the last year (i.e. since around mid-2022), it was mainly people with a high AIX who have gained this experience. 71% is an impressively high figure: this indicates that the AI transformation was initiated early on for these job areas. For respondents with a medium and low AIX value, the rate is considerably lower, around 33 and 50 percentage points respectively. Nevertheless, these values still seem high overall - after all, the broad AI boom with ChatGPT had only just started in the months before the survey, and there was hardly any time to react to this with new and targeted training.

- Finally, the level of experience in the competence field "Instrumental digital competence" is also surprisingly high. Here, respondents were asked to respond to the statement "I use AI applications as an instrument to perform my tasks". In the groups with a high or medium AIX value, 93.8% and 76.5% respectively rated this as true or completely true.

- The fact that "cooperation competence" is at the very bottom of the scale of all 12 competence fields in all three AIX groups is not surprising insofar as there has been little opportunity to gain experience with AI projects up to this point. Rather, it is surprising that 59% of people with a high AIX have gained experience here. (The likewise uniformly low value for "self-competence" can be explained by the specific question: respondents were asked whether they had gained experience in determining their preferences when interacting with AI proposal systems).

The ranking list of competences is then presented. This shows which competences are saturated with experience by more than half of the respondents and where there is still potential for development. Communication skills have the highest experience rate, while self-competence and cooperation skills are less well-developed. A differentiated picture of the skills landscape thus emerges, providing an insight into the status and possible future educational priorities.

Mean values for Experience		
Communication Competence	84,1	++
System design Competence	70.00	+
Critical digital Competence	69,0	+
Decision-making Competence	68,7	+
Instrumental digital Competence	62,3	+
Critical Thinking	59,1	O

[9] Percentages refer to the TOP2 values: i.e. answers that show experience in the respective Assign "strongly agree" or "agree" to the competence field.

Initiative Competence	43,7	-
Ethical Competence	38,9	-
Creative design Competence	38,1	-
Learning Competence	35,8	-
Self-competence	29,9	-
Cooperation Competence	27,7	-

Figure 45 Ranking of the 12 competence fields according to mean values for AI experience (median = 55.9)

7.2 Sovereignty as a competence dimension

The concept of sovereignty in the context of AI Future Skills is essential for understanding and promoting the autonomy and self-determination of individuals in an increasingly digitalized world. In the following chapter, we examine how sovereignty - defined as the ability to interact confidently and self-determinedly with AI technologies - manifests itself and which factors influence it. We shed light on how self-assessment of one's competence in dealing with AI serves as an indicator of sovereignty and how this shapes both individual action and social participation.

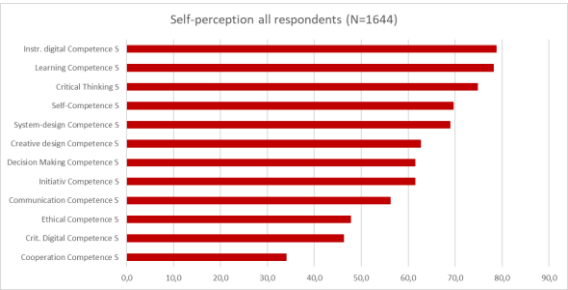


Figure 46 Self-perception of own sovereignty about Future Skills. Grading across 12 competence fields

The data on confidence in dealing with AI-related skills shows the following:

- Strong decision-making skills (61.4%) indicate that most respondents are confident in involving AI assistance in work decisions.
- High scores in Learning Competence (78.2%) and Critical Thinking (74.8%) reflect confidence in their judgment and continuous learning in the field of AI.
- Ethical (47.7%) and self-competence (69.6%) are medium-high, indicating that many respondents make ethical considerations and use AI according to personal preferences.
- Instrumental Digital Competence (78.8%) shows a high level of confidence in the use of new AI applications.
- In contrast, Critical Digital Competence (46.2%) is lower, which could indicate uncertainty when evaluating new AI systems.
- System Design Competence (68.9%) and Creative Design Competence (62.6%) show that the majority can incorporate AI into the design of work processes.
- Initiative competence (61.4%) and Cooperation competence (34.0%) vary, indicating different degrees of initiative and cooperation in AI projects.
- Communication competence (56.2%) indicates that more than half of the respondents feel confident when it comes to AI exchange.

These values reflect how confident individuals feel in various aspects of AI skills and represent a measure of their self-assessment of their abilities.

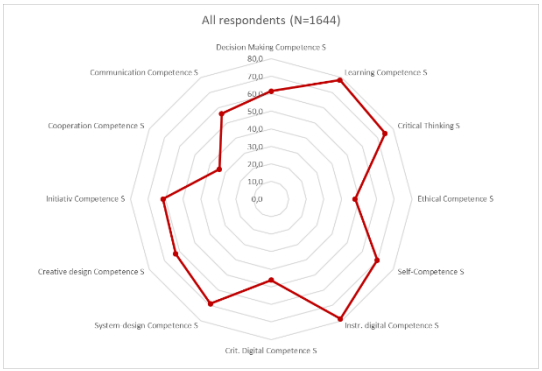


Figure 47 Self-perception of own sovereignty in relation to Future Skills: grading across 12 competence fields as a spider diagram

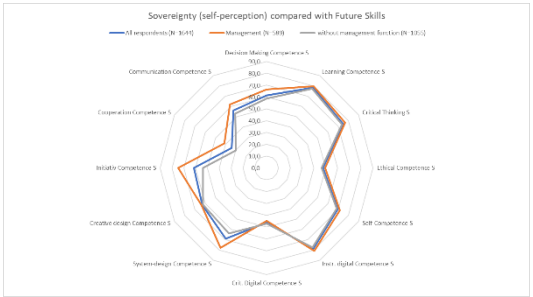


Figure 48 Self-perception of own sovereignty about Future Skills: respondents with and without a management function in comparison (spider diagram)

The evaluation of the data on confidence as a function of position shows that managers feel more competent in almost all areas than employees without a management function. The highest values for both groups are found in learning competence and instrumental digital competence, which indicates general confidence in their ability to continue training and use digital tools. The relatively low level of ethical competence overall is striking but with a slight lead among managers. Critical digital competence is the only category in which employees without a management function score higher, which could indicate that they view the effects of AI in their day-to-day work somewhat more critically. Cooperation skills are low overall, with managers scoring significantly higher, which suggests greater involvement in AI projects and teamwork. Communication skills are also higher among managers, which indicates greater confidence in dealing with AI-related discussions.

How confident do the respondents feel about the 12 areas of competence? This indicates where there is a particular need to strengthen their competences.

The data shown below in the spider diagram reflects the respondents' self-assessment of their skills in dealing with artificial intelligence, broken down into high, medium, and low according to the activity index (AIX). People with a high AIX rate their confidence significantly higher in all areas of competence, which indicates that an active approach to AI technologies increases self-confidence in their abilities. This is particularly noticeable in the areas of instructional digital competence and system design competence, which are essential aspects in the handling and understanding of AI systems.

As expected, respondents with a low AIX have lower sovereignty scores in all areas, especially in Critical Digital Competence and Cooperation Competence. This could indicate uncertainties in the understanding and collaborative use of AI.

Ethical competence is lower overall than other areas, which emphasizes the need to place a stronger focus on ethical aspects of AI in education and training programs. Self-competence, the ability to adapt AI systems to personal preferences, is more pronounced among respondents with a high AIX, which suggests a higher level of control over the technology.

Interestingly, communication competence shows relatively high values across all AIX levels, reflecting a basic willingness to communicate about AI topics, regardless of the level of technical experience. The results suggest that active experience with AI strengthens the perceived sovereignty in all areas and thus represents a central element in the promotion of AI skills.

A look at the details of the spider diagram first shows that the three AIX levels are recognizable here as concentric rings: the distance is between 10 and 15 percentage points in each case. In eight areas of competence, the values are between 60% and 90% for the group with a low KI activity level, around 80% for a medium AIX value, and 90% and higher for a high AIX value.

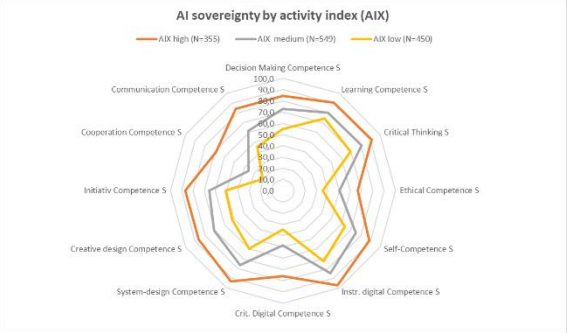


Figure 49 Self-perceived sovereignty in the 12 competence fields in relation to the AI activity index

- Overall, the degree of sovereignty that respondents from the random sample ascribe to themselves appears to be quite high. However, the points at which the rings in the diagram flatten out significantly are conspicuous because the feeling of sovereignty is lower.
- These values are lowest, especially among those with a medium and low level of AI activity, for "cooperation competence", which can be explained by the lack of concrete AI projects. However, the feeling of sovereignty is also significantly lower than in most other areas of competence concerning "critical digital competence", "communication competence" and "ethical competence". It is not so much the specific challenges associated with AI technologies that appear to be

unsettling, but rather the fundamental changes that go hand in hand with them.

- The approval ratings for "self-competence", "creative design competence", "initiative competence" and "decision-making competence" are strikingly high relative to the respective AIX value. The values here are over 85% (AIX high), between 65% and 75% (AIX medium), and between 45% and 55% (AIX low). In each case, these are skills in which the focus is less on technical familiarity with AI and more on self-confidence and the will to actively deal with it. At least in our random sample, there seems to be a "let's get on with it" mood, which is all the higher the more actively people have already dealt with AI.
- A discrepancy between experience and sovereignty values can be seen in "critical digital competence" concerning AI, which is about being able to see through AI systems. The interviewees ascribe a relatively high level of experience to themselves here, they already deal critically with AI, but this is not yet associated with a corresponding increase in the feeling of sovereignty. (However, 48.6% and 35% respectively ascribe this ability to themselves).
- In two areas, respondents with medium and low AIX ascribe higher values to themselves overall than would correspond to their level of experience: in "critical thinking", but also in "learning competence". They therefore feel up to the challenges ahead and are willing to undergo further training in AI.

As part of the analysis of sovereignty values in dealing with AI, the respondents' self-perceptions in different areas of competence become apparent. Instrumental digital competence and learning competence are at the top of the ranking, which indicates a pronounced confidence in their ability to use and understand AI. Critical digital competence and cooperation competence, on the other hand, are rated less highly, which indicates development opportunities in these areas.

Mean values for Sovereignty		
Instrumental digital Competence	78,8	+
Learning Competence	78,2	+
Critical Thinking	74,8	+
Self-competence	69,6	+
System design Competence	68,9	+
Creative design Competence	62,6	+
Decision-making Competence	61,4	O
Initiative Competence	61,4	O
Communication Competence	56,2	O
Ethical Competence	47,7	O
Critical digital Competence	46,2	O
Cooperation Competence	34,0	-

Figure 50 Ranking of the 12 areas of competence according to mean values for self-perceived sovereignty (median = 56.4)

7.3 Future significance of AI skills

In this chapter, we look at the prospects and the importance that respondents attach to AI-related Future Skills. The dimension of future significance deepens our findings from the experiences and perceived sovereignty by looking at the values and anticipated relevance of AI skills for future challenges. By shedding light on individual and collective expectations of the future potential of AI, we identify which skills are considered essential for shaping and participating in a future permeated by AI. This section thus reflects how individuals see and position themselves in a dynamic world influenced by AI.

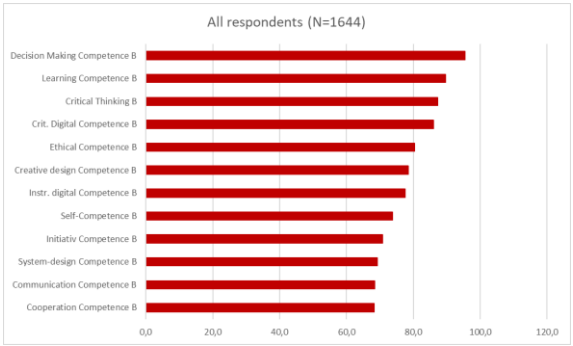


Figure 51 Assessment of the future significance of AI-related Future Skills (12 competence fields) in gradation (all respondents)

The data on the assessment of the future importance of AI-related skills reflects a strong

awareness and high expectations among respondents. Decision-making competence, which describes the confidence in the ability to use AI systems to support oneself, is rated as extremely relevant at 95.4%, which underlines its central role in the future working environment. Learning competence follows closely with 89.7%, which emphasizes the importance of continuous training in the field of AI. The situation is similar to critical thinking, which is rated at 87.3% and emphasizes the need to critically question AI systems.
Ethical competence, rated at 80.4%, shows that a strong ethical awareness is considered increasingly important for the responsible use of AI. Self-competence and the ability to recognize the transition between self-determination and heteronomy through AI are also rated as significant (73.7%), which emphasizes the importance of autonomy in dealing with AI.
Instrumental digital competence, which describes the practical application of AI in the workplace, is considered crucial by 77.6% of respondents. Critical digital competence (86.1%) and system design competence (68.9%) reflect the need for a deeper understanding and active involvement in the design of AI systems.
Initiative competence and cooperation competence show that respondents value the importance of initiative and teamwork in the context of AI, with the former rated at 70.8% and the latter at 68.2%. Communication skills, rated at 68.4%, show that communication skills in the field of AI are considered essential for the future.
This data illustrates the general expectation of respondents that these skills will be key elements for success in a professional field increasingly influenced by AI.

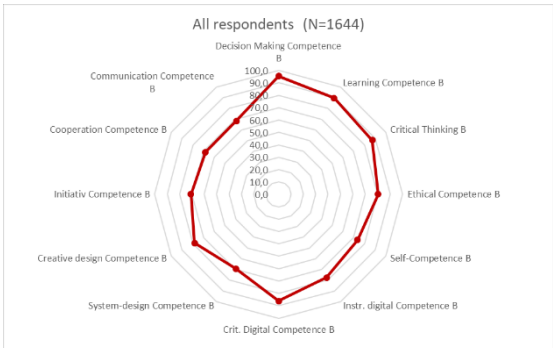


Figure 52 Assessment of the future significance of the 12 areas of expertise (all respondents, N=1644)

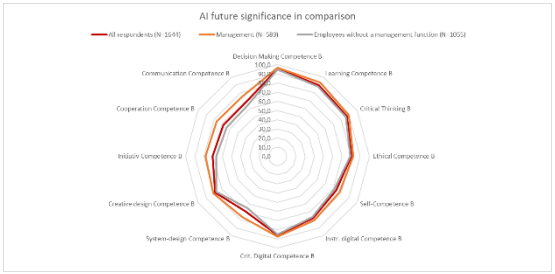


Figure 53 Assessment of the future significance of the 12 areas of expertise for respondents with and without a management function

The interpretation of the data shows that managers give a higher assessment of their skills across all areas of competence than employees without a management position. For example, managers rate their decision-making skills higher (96.6% compared to 94.8%), which could indicate that leadership roles strengthen confidence in one's decision-making ability. The situation is similar to learning competence and critical thinking, where managers also have higher scores.
What is striking is the clear difference in the assessment of system design competence, where managers score 76.4% compared to 65.2% for employees without a management position, which underlines the importance of this competence for management tasks. The initiative competence is also much more pronounced among managers (78.3% compared to 66.6%), which indicates a higher tendency to act proactively and initiate new approaches.
Cooperation skills and communication skills also scored higher among managers, reflecting the importance of collaboration and communication in leadership roles. This data suggests that positions with leadership responsibility are not only associated with higher competence ratings but also require specific competences that are critical for management and leadership within an organization.
How do the respondents assess the future significance of AI for each of the twelve areas of competence and in relation to their AI activity index?
The available data illustrates the correlation between the AI activity index (AIX) and the perceived future importance of various competences. People with a high AIX value recognize the importance of all the skills surveyed much more strongly than those with a lower AIX or non-users. Decision-making skills and learning

skills are considered important by almost all respondents, which underlines the central role of these skills in a future increasingly influenced by AI.

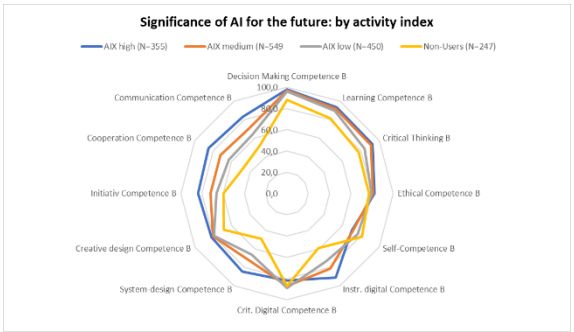


Figure 54 Assessment of the future significance of the 12 areas of expertise in relation to the AI activity index

The high assessment of Critical Digital Literacy even among non-users could indicate that a basic understanding of AI technology and its critical evaluation is considered universally important, regardless of the level of direct interaction with AI.

Interestingly, self-competence is rated highest among non-users, suggesting that this group feels or strives for a high degree of self-determination, perhaps precisely because they interact less directly with AI technologies.

In the area of cooperation skills, there is a big difference between the AIX groups and the non-users. This could mean that active AI use also influences the perception of teamwork and collaborative projects in the context of AI.

Overall, the data reflects the expectation that AI-related skills will contribute significantly to professional success in the future, and this is seen as even more pronounced by people who are more involved in AI.

Three points stand out in this third spider diagram:

- The values are consistently high for all AIX groups. Even people with a low level of AI activity, who on average also have significantly less experience and perceived sovereignty, hardly rate the future relevance of AI lower than the others.

- The assessments are very uniform. AI activity levels (AIX) have very little influence on the answers here. Significantly higher assessments of importance (by a good 10% on average) are only found in the group with a high AIX, and even this only applies to five of the twelve competence fields. These all have to do with task areas that particularly affect managers who are already focusing on future transformation processes: "Initiative competence", "System design competence", "Cooperation competence", "Communication competence" and "Instrumental digital competence".

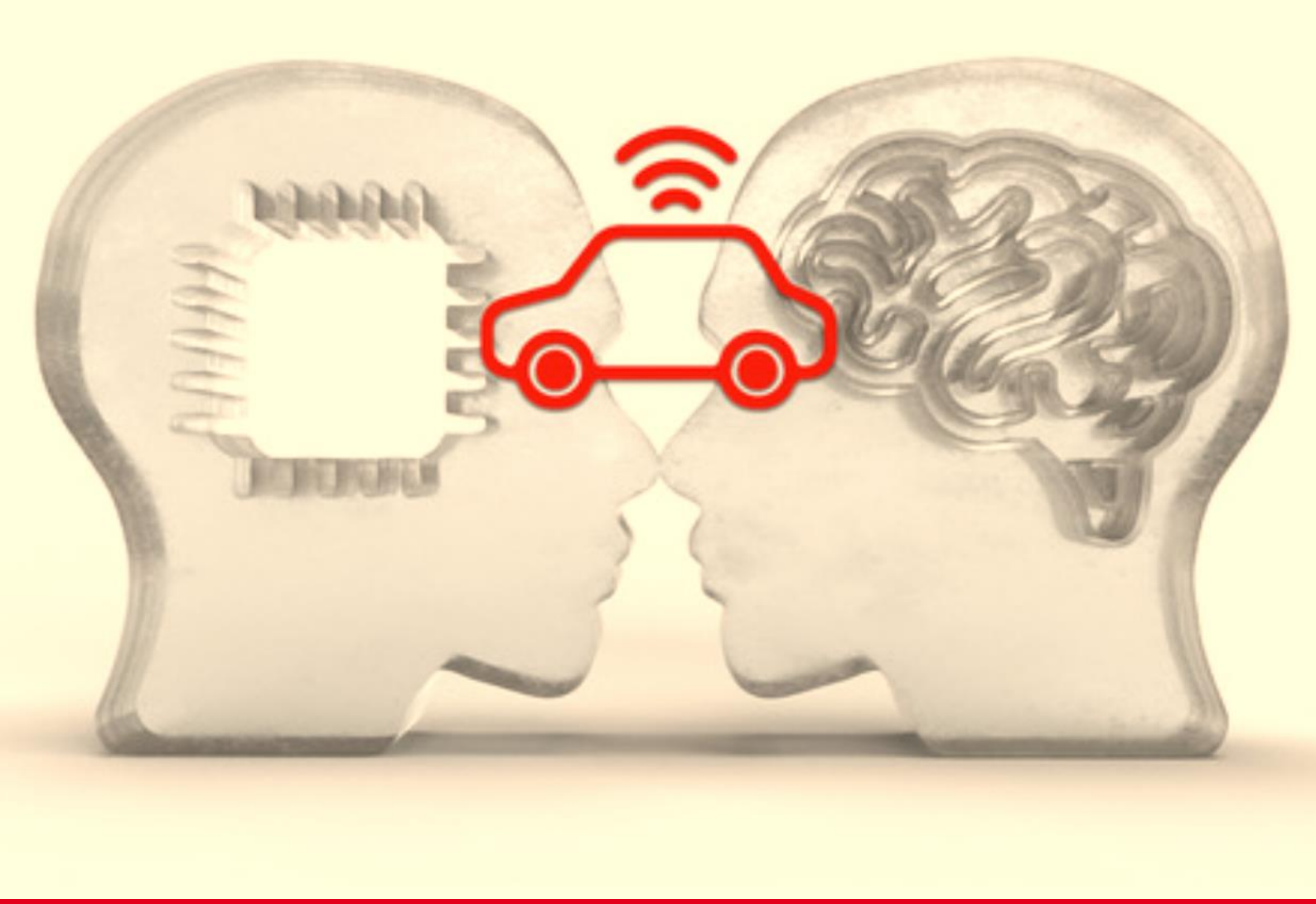
- Respondents unanimously consider AI-related "decision-making skills" (with values between 96% and 98%) and AI-related "learning skills" (90% to 93%) to be highly relevant for the future. This is followed by "critical thinking" and "instrumental digital competence". The consistently high values for the importance of "ethical competence" should also be emphasized: between 79.5% and 82%.

The results on the future importance of AI Future Skills show that decision-making competence is rated as particularly relevant at 95.4%, which indicates that the ability to make AI-supported decisions is seen as critical for the future. High scores for learning competence (89.7%) and critical thinking (87.3%) underline the importance of continuous learning and analytical questioning in the context of AI.

Mean values for future significance		
Decision-making Competence	95,4	++
Learning Competence	89,7	++
Critical Thinking	87,3	++
Critical digital Competence	86,1	++
Ethical Competence	80,4	+
Creative design Competence	78,5	+
Instrumental digital Competence	77,6	+
Self-competence	73,7	+
Initiative Competence	70,8	+
System design Competence	69,2	+
Communication Competence	68,4	+
Cooperation Competence	68,2	+

Figure 55 Ranking of the 12 areas of expertise according to mean values of future importance (median = 81.9)

Ethical considerations, represented by ethical competence (80.4%), are also seen as increasingly important, while self-competence and creative design competence highlight the importance of individual adaptation and innovative use of AI. Cooperation and communication skills, which are considered fundamental for collaboration in AI projects, are considered important in the future by more than two-thirds of respondents, which emphasizes the relevance of teamwork in a working world influenced by AI.



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8. Discrepancy analyses: Future Skills in comparison between importance and experience or sovereignty

The assessment of competences along the three dimensions of experience, sovereignty, and future significance can be linked in such a way that the differences in significance between these dimensions become recognizable. The significance of the future plays a central role here. By relating the other two dimensions to the importance of the future, discrepancies emerge that highlight the importance of certain skills on the one hand and shed light on the respondents' current experiences and their self-assessment about the Future Skills on the other.

To visualize these relationships, the action relevance matrix was developed, which places both dimensions in relation to each other. This concept serves as a tool to enable managers in organizations and educational institutions to carry out a structured analysis and prioritization of skills and corresponding measures. In the context of our study on Future Skills, the action relevance matrix provides a differentiated insight into the assessment of various skills by the employees surveyed, concerning their future importance and their current experience. This facilitates the effective allocation of resources by prioritizing areas with a high need for action. The average values of the assessments of Future Skills, which are based on a scale of 1 ("strongly disagree") to 4 ("strongly agree"), reflect the respondents' collective assessment of the dimensions "experience", "confidence", and "future relevance" for each of the skills areas surveyed. The "experience" dimension shows the extent to which the respondents feel familiar with the competences based on their previous experience (e.g. through application in everyday working life). "Confidence" describes how respondents rate their level of competence in the experienced Future Skills. "Future importance" reflects the importance the respondents attach to their individual skills concerning future challenges in their lives and work.

Table 4 Mean values of the competence fields for the Future Skills

	Significance for the future	Experience	Sovereignty
Decision-making Competence	3,1	2,7	2,8
Learning Competence	3,2	2,9	3,0
Critical Thinking	3,0	2,9	2,9
Ethical Competence	3,1	2,3	2,5
Self-competence	3,4	2,8	2,9
Instrumental digital Competence	3,3	2,2	3,0
Critical digital Competence	3,4	2,7	2,5
System design Competence	3,2	2,3	2,9
Creative design Competence	3,1	2,2	2,7
Initiative Competence	3,0	2,4	2,7
Cooperation Competence	2,9	2,0	2,2
Communication Competence	3,0	3,1	2,7
Average of the mean values	3,1	2,5	2,7

The mean values can be used to identify which skills are considered particularly relevant and in which areas the respondents have already gained experience. If one now calculates the respective average of all mean values of a dimension, e.g. "Importance for the future" with 3.1, one obtains the axis value for this dimension. All values for this dimension are now either above or below average. If you proceed in the same way with the second dimension, you obtain a second axis of average values. Both axes together divide a four-quadrant field. The mean values for the competences can then be assigned to the four fields of the action relevance matrix. We have named these as follows:

- Potential area (above-average experience, below-average importance for the future): Competences in this area are regarded by the respondents as currently well mastered, but less important for the future. They could offer potential for optimization but are not a priority for investment in further training.
- Performance area (above-average experience and importance for the future): This is where the competences lie for which both current experience and the assessment of their future relevance are high. These competences are core strengths and should be further promoted to strengthen the position of the organization or the individual.
- Development area (above-average future relevance, below-average experience): Competences that are considered very important in the future but are currently not sufficiently mastered fall into this area. These skills require targeted development and training measures to ensure future competence.
- Marginal area (below-average experience and importance for the future): Competences in this field are rated as low in terms of both current experience and future importance. They do not represent immediate development goals but may become more relevant in the long term.

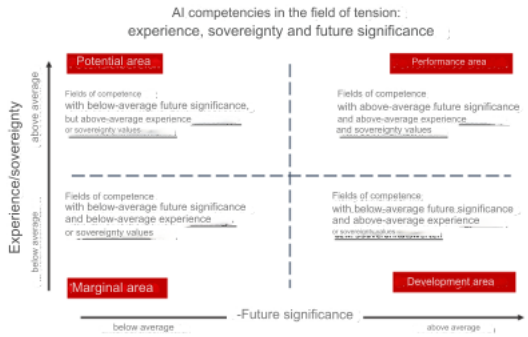


Figure 56 Structure of the action relevance matrix for the evaluation of the results for the 12 competence fields in relation to self-perceived sovereignty

Figure 56 shows the principle of the 4-field structure of the action relevance matrix. Measures can be prioritized according to whether they are of below-average or above-average importance. The following two 4-field matrices were created according to the following principles:

- The horizontal axis represents the mean value of future importance
- The vertical axis represents the overall mean value of all individual mean values of the respective dimension experience (average of the mean values: 2.5) or sovereignty (average of the mean values: 2.7)

8.1 Discrepancy analysis: Sovereignty about future significance

Performance area:

- Learning competence S (future relevance: 3.2, confidence: 3.0)
- Instr. digital competence S (importance for the future: 3.3, confidence: 3.0)
- Self-competence S (importance for the future: 3.4, sovereignty: 2.9)
- System design competence S (Importance for the future: 3.2, Sovereignty: 2.9)
- Decision-making competence S (Importance for the future: 3.1, Sovereignty: 2.8)

Development area:

- Crit. Digital competence S (Importance for the future: 3.4, sovereignty: 2.5)
- Creative design competence S (importance for the future: 3.1, sovereignty: 2.7)
- Ethical competence S (importance for the future: 3.1, sovereignty: 2.5)

Potential area:

- Critical thinking S (future relevance: 3.0, sovereignty: 2.9)
- Initiative competence S (future relevance: 3.0, confidence: 2.7)
- Communication skills S (Importance for the future: 3.0, Confidence: 2.7)

Marginal area:

- Cooperation competence S (Importance for the future: 2.9, Sovereignty: 2.2)

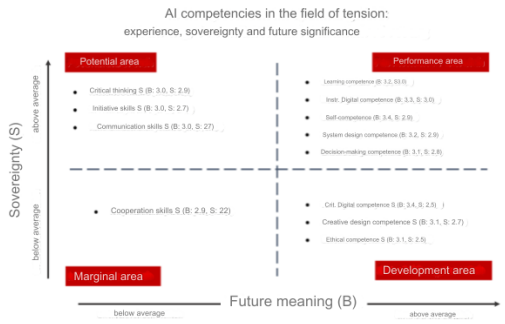


Figure 57 Matrix for the evaluation of the results for the 12 competence fields: self-perceived sovereignty in relation to importance for the future

8.2 Discrepancy analysis: Experience in relation to future interpretation

Potential area:

- Communication skills E (importance for the future: 3.0, experience: 3.1)
- Critical thinking E (future relevance: 3.0, experience: 2.9)

Performance area:

- Self-competence E (future relevance: 3.4, experience: 2.8)
- Crit. Digital competence E (future relevance: 3.4, experience: 2.7)
- Learning competence E (future relevance: 3.2, experience: 2.9)
- Decision-making competence E (importance for the future: 3.1, experience: 2.7)

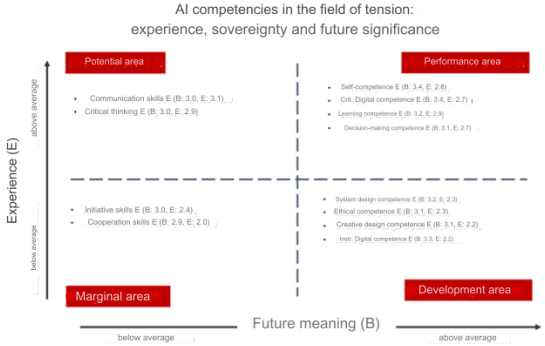


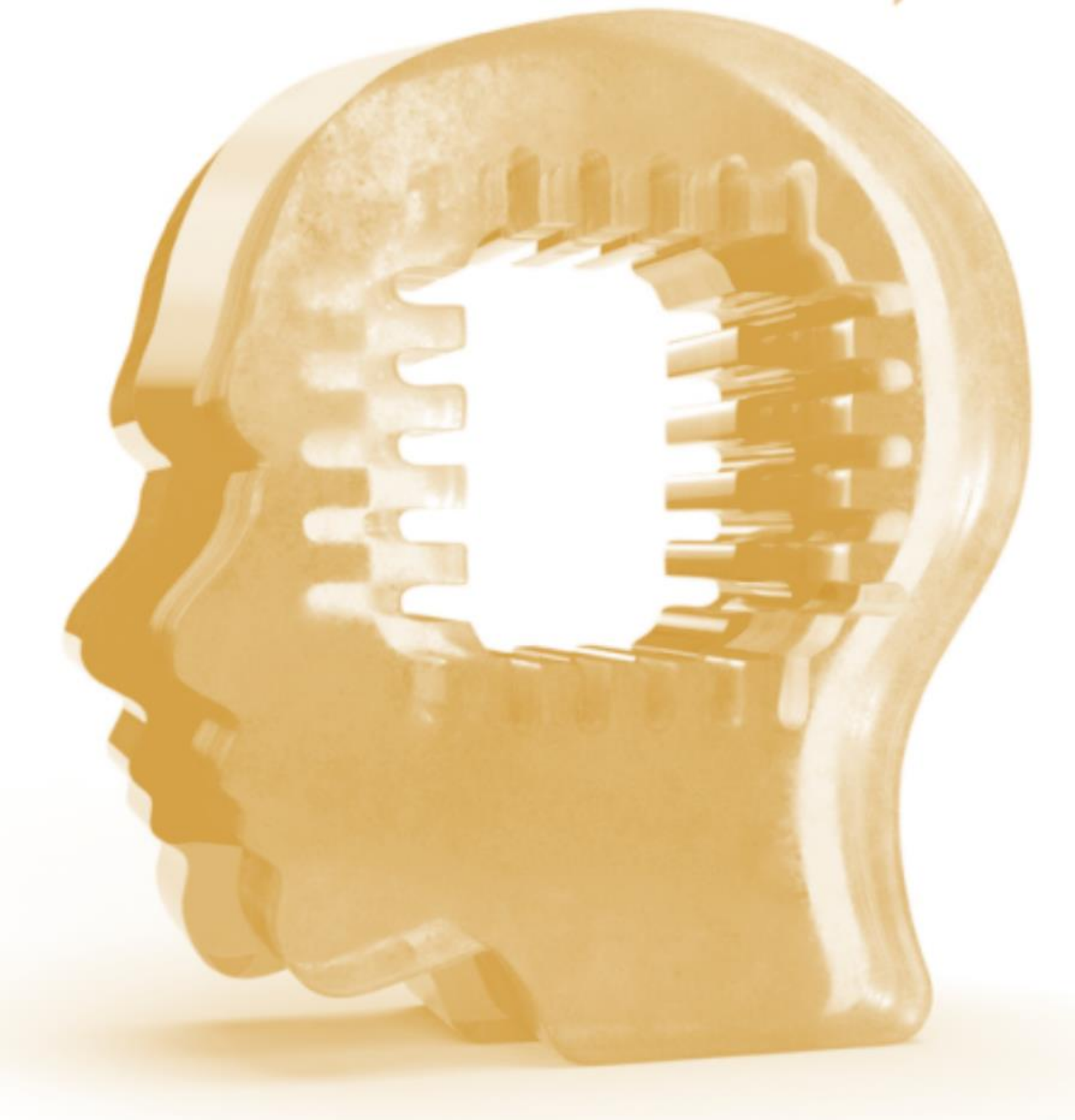
Figure 58 Matrix for the evaluation of the results for the 12 areas of expertise: Experience in relation to future importance

Development area:

- System design competence E (importance for the future: 3.2, experience: 2.3)
- Ethical competence E (future relevance: 3.1, experience: 2.3)
- Creative design competence E (importance for the future: 3.1, experience: 2.2)
- Instr. digital competence E (importance for the future: 3.3, experience: 2.2)

Marginal area:

- Initiative competence E (future relevance: 3.0, experience: 2.4)
- Cooperation competence E (future relevance: 2.9, experience: 2.0)



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9. Summary

The AIComp study provides comprehensive insights into the status and development potential of AI skills in Germany. The results show that there is already a broad basis of experience and skills in dealing with AI technologies across different age groups, genders, professional positions, and fields of activity. This provides a solid basis for the further integration of AI into the labor market and society.

The diversity of the social statistical characteristics of the participants lends additional depth to the study results. The positive attitude towards AI, the wide range of AI-relevant skills demonstrated in different areas of competence, and the awareness of the importance of education and training in the field of AI are encouraging signs that Germany can take advantage of the challenges and opportunities of AI.

However, certain gaps and areas of development are also becoming apparent, particularly concerning "critical digital competence" and "ethical competence" in dealing with AI. The need to strengthen these areas through targeted education and training initiatives is obvious to ensure the comprehensive and responsible use of AI in all sectors.

The objective of this study, the research of Future Skills in the context of artificial intelligence, can be considered complete. A meaningful skills portfolio was identified that is relevant from the respondents' perspective. In addition, assessments of these skills were collected as part of the quantitative survey. The analysis of the data distribution shows that the selected list of competences makes it possible to effectively divide the participants into groups in terms of their experience, self-perception, and predicted importance for the future. These results underline that the conceptual constructs used are statistically suitable to adequately reflect the diversity of opinions within the study participants.

Finally, the study shows the importance of interdisciplinary approaches and the need to integrate AI skills into all levels of education and professional fields. To secure and further expand Germany's position as a leading AI nation, a coordinated effort is required from all those involved - educational institutions, companies, politics, and the public. The AIComp study provides a valuable basis and orientation for this.

9.1 Participants in the study

The socio-statistical characteristics of the participants in the AIComp study provide a broad spectrum of demographic information that is relevant for the interpretation of the study results. The most important characteristics of the participants are summarized below:

- Age structure: The participants cover a broad age spectrum, with the middle age groups (30-59 years) being more strongly represented, which indicates a working population. The largest group is the 50-59 year-olds, followed by the 30-39 year-olds and the 40-49 year-olds, which underlines the level of experience of the participants.
- Gender distribution: There is an almost balanced distribution between male (approx. 54%) and female (approx. 43%) participants, with a small number of people who identify as diverse or did not specify.
- Organization size: The study included participants from a wide range of organizations of different sizes. Large companies as well as medium-sized and small companies were represented.
- Professional position: The study included a wide range of professional positions, including team leaders, managers, HR managers, project managers, engineers, and managing directors, reflecting the diversity of perspectives and experiences.
- Fields of activity: Participants came from a variety of fields of activity, including science and research, IT and mathematics, education, office and administration, management and consulting, and business and finance.

These socio-statistical characteristics show that the participants represent a broad spectrum of age groups, genders, organizational sizes, professional positions, and fields of activity. This contributes to the depth and breadth

of insight that the study provides in terms of AI skills and experience.

9.2 Setting values for AI

The opinions of respondents on AI in general (see 6.4) provide information on attitudes and expectations regarding artificial intelligence. Interestingly, awareness of the rapid development of AI technologies and their impact on the labor market is widespread: 87% of respondents believe that AI will influence their work in the near future. Above all, most of those surveyed view the use of AI in their area of work positively, which initially suggests a general acceptance of AI and a positive perception of efficiency gains and benefits in the world of work. Despite this positive assessment, a majority fear that AI could lead to job losses (58% of respondents agreed with this statement). Opinions on the influence of AI on important decisions in private life also differ.

Furthermore, a notable number of respondents believe that AI will one day be superior to human intelligence, reflecting the public debate about the long-term impact of AI and its ethical implications. These findings signal a wide range of expectations and concerns that are highly relevant for understanding the social dynamics of technology adoption and for guiding policy and education measures in the age of digitalization.

To summarize, the results of the survey show a generally positive attitude towards AI in the work context, while also highlighting challenges and concerns about the personal and social impact of AI. These mixed feelings towards AI underline the need to carefully weigh up the opportunities and risks and develop strategies to promote AI skills and manage the potential impact of AI on the world of work and beyond.

9.3 AI activity index as a meaningful predictor of AI Future Skils

The analysis of the AI Activity Index (AIX) in the AIComp study provides valuable insights into how the experience and competence in dealing with AI varies in different areas of competence and groups. The AIX serves as a tool to measure the intensity and frequency with which individuals use and understand AI technologies. The key findings on AI experience in relation to the AIX include

- Variation in AI experience by AIX level: People with a high AIX score have more experience in almost all the AI skills areas examined. This shows that more intensive involvement with AI leads to broader and deeper experience across a range of competences.
- Higher competence values with a high AIX: Participants with a high AIX value show particularly strong competences in areas such as decision-making competence and instrumental digital competence. This indicates a close connection between the active use of AI and the development of specific AI-related skills.
- Decline in competence values with falling AIX: The study found that the values for various competences also fall with falling AIX, particularly for learning and initiative competence. This indicates that less engagement with AI is associated with lower competence levels.
- Critical digital competence across all AIX groups: Interestingly, critical digital competence, i.e. the ability to penetrate AI systems critically and analytically, is comparatively high across all AIX groups. This shows that a basic critical understanding of AI technologies is present regardless of the degree of active use.
- Communication competence as a universal skill: Communication competence in the context of AI remains relatively high across all groups, which indicates that exchanges on AI topics also take place among those who have less practical experience with AI.

The results of the AI activity index underline the importance of active experience with AI for the development of AI skills. They also show that certain skills such as critical digital literacy and communication skills are important foundations that can be developed regardless of the intensity of AI use.

9.4 Future Skills

The AIComp study offers a comprehensive analysis of the role of Future Skills in the context of digital transformation with a particular focus on the requirements arising from the increasing integration of artificial intelligence (AI) into the world of work and life. By looking at the three dimensions of experience, sovereignty, and future significance, the study not only enables a detailed understanding of the current state of AI skills but also provides valuable information on development potential and training needs. The key findings are explained in more detail below.

Experience with AI-related Future Skills
An examination of the experience dimension reveals a differentiated picture of practical engagement with AI technologies. Most respondents show a high level of activity in communicative competence, which indicates that discussions and exchanges about AI are an integral part of professional and, in some cases, private interactions. In addition, a significant proportion of the study participants reported extensive experience in the use of AI to solve specific problems, which is particularly evident in the areas of system design competence and critical digital competence.
It is also interesting to note that experience with AI is relatively evenly distributed across different age and occupational groups, which underlines the ubiquitous importance and penetration of AI technologies in the modern working world. However, managers tend to have a broader range of experience, reflecting their role in implementing and managing AI-supported processes.

Personal sovereignty about AI Future Skills
The sovereignty dimension measures how competent and self-determined the respondents feel in dealing with AI. High scores in the areas of learning competence and critical thinking demonstrate a strong confidence in their own ability to continuously learn and critically question AI systems. This is particularly relevant in a rapidly changing technology landscape where continuous learning and adaptability are crucial.

The high self-perception of instrumental digital competence also shows that many respondents are confident in their ability to effectively integrate new AI applications into their everyday work. However, it is striking that despite the overall high level of confidence in many areas, certain skills such as ethical competence and cooperation skills are rated lower. This indicates areas in which further education and awareness-raising measures are required to strengthen individual and collective competence in dealing with AI.

The future importance of AI skills
The assessment of the future importance of AI-related skills reflects the respondents' expectations and values regarding the relevance of these skills in the future world of work. Decision-making skills and learning skills are considered particularly important, which underlines the central role of AI support in decision-making processes and the need for lifelong learning in a technology-driven society.
The high rating of ethical competence also shows that a responsible approach to AI and the consideration of ethical aspects are seen as crucial for the future. This underlines the importance of educational initiatives that promote not only technical skills but also ethical and social competences.

Due to the amount of data obtained, the specific AIComp competence model will be published in a second part of the report see www.ai-comp.org

9.5 Discrepancy analyses as a method for identifying support needs

The discrepancy analyses of the AIComp study place a particular focus on identifying specific skills deficits and experience gaps to define precise educational and development needs on this basis. The analysis of the self-perception of sovereignty in various fields of competence - such as critical digital competence, cooperation competence, learning competence, and instrumental digital competence - in comparison to

their predicted future importance enables a detailed consideration of the areas in which intensive support measures are necessary. An action relevance matrix is used as an analysis tool to illustrate the importance and urgency of promoting skills and thus identify priority areas for action.
Critical digital competence as a priority field of action is characterized by its central importance. This competence, which includes the ability to understand and critically scrutinize AI systems, is seen as crucial for the future. At the same time, there is a significant gap in current sovereignty, which indicates an urgent need for further training initiatives in this area.
The action relevance matrix is used to differentiate between areas of competence by comparing the future relevance of individual competences with the current level of sovereignty and practical experience. Areas with high future relevance and at the same time low current sovereignty or experience, such as cooperation skills, are particularly emphasized. This is considered important but shows deficits due to a lack of practical application experience in AI projects. Concerning the implications for education and personnel development, the results underline the need for targeted support in areas of competence where there is an acute need for action. This includes targeted further training and qualification to increase sovereignty and practical experience in priority competence areas such as critical digital competence and cooperation competence, but also learning competence and instrumental digital competence.
In summary, the gap analysis of the AIComp study highlights the urgent need for targeted and strategically oriented promotion of specific skills. This is necessary to prepare individuals and organizations for the complex challenges of an AI-driven future. The identification of skills deficits and experience gaps forms an essential basis for the development of effective training and further education programs to improve the ability to act and adapt to future technological developments.

9.6 Further deepening of the Future Skill concept

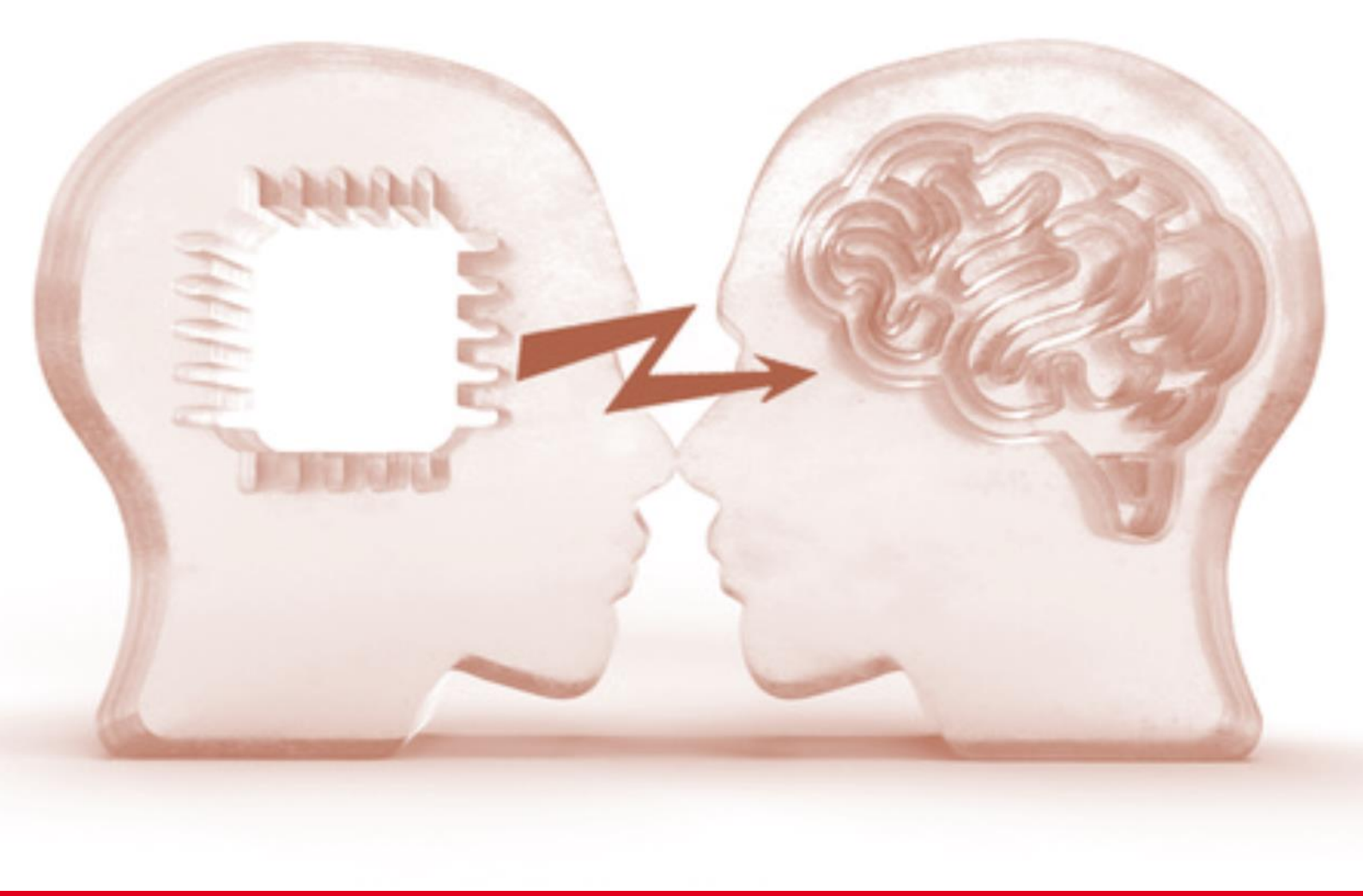
In summary, the AIComp study represents an important step towards further developing the concept of Future Skills and making it usable for the field of AI. By providing a stronger theoretical foundation and clarifying definitions, it creates the basis for the targeted development of skills that are indispensable for mastering future challenges. The establishment of a Future Skills model for artificial intelligence (AI) by the AIComp study marks a significant step forward in the discussion and conceptual anchoring of the term and concept of Future Skills. By applying fundamental concepts of Future Skills specifically to the field of AI, the study makes an important contribution to the further development of this field of research. In doing so, it explicitly addresses existing points of criticism relating to the theoretical foundation and definitional vagueness of the Future Skills concept. The study plays an important role in that it not only takes up the concept of Future Skills but also substantiates it in terms of educational theory and skills theory. This is achieved through a clear definition and a targeted operationalization of the skills relevant for dealing with AI. This specification creates a solid basis on which future educational strategies and curricula can be developed. The explication of the individual components of the Future Skills Model for AI helps to transfer the concept from the realm of vague generalizations into the context of applicable and measurable skills.
The AIComp study responds to the previously expressed criticism of the lack of theoretical foundation of the Future Skills concept and its lack of definition. By establishing a clearly defined and well-operationalized Future Skills concept for the field of AI, the study closes a significant gap in previous research. This methodological approach makes it possible to treat Future Skills not only as an abstract concept but also to discuss them specifically regarding the necessary competences in dealing with AI technologies.
By anchoring the Future Skills model in an educational theory and action competence theory framework, a comprehensive understanding can be developed of which competences will be required in the digitally transformed world of tomorrow. This approach makes it possible to understand Future Skills as an integral part of

lifelong learning and to place them at the center of future-oriented educational policy and practice. Especially in the field of AI, it is necessary to continuously adapt educational offerings to the changing requirements of the labor market and society.

9.7 Further results

The AIComp study provides an in-depth insight into the status and future demand for AI skills in Germany. Further important insights were gained in the process:

- Gender bias: The discrepancy in the AI activity index between men and women identified in the AIComp study raises important questions about gender dynamics in the engagement with technologies, particularly with artificial intelligence (AI). The lower scores of women compared to men on the AI Activity Index can be explained by a variety of factors, both cultural and structural. It is important to emphasize that these differences are not due to intrinsic abilities or interests, but to the effect of social, cultural, and institutional influences. To reduce the gender gap in the AI activity index, targeted strategies are needed that address the factors mentioned above. These include promoting female role models in AI, creating inclusive and supportive learning environments, breaking down stereotypes through education and awareness-raising, and providing resources specifically geared towards supporting and promoting women in AI professions. These efforts must be supported by educational institutions, businesses, policymakers, and society to create a more inclusive and equitable AI ecosystem where people of all genders can participate and succeed equally.
- Teaching AI skills in a targeted manner: Concerning the teaching of AI Future Skills, the AIComp study shows target group-specific differences in experience with artificial intelligence. These findings not only underline the need for target group-specific learning opportunities but also the importance of adaptive didactic approaches for the effective development of AI Future Skills. To cope with the existing differences, didactic flexibility is required that encompasses a variety of teaching and learning methods - from practice-oriented workshops that address real-world problems to online courses that enable flexible participation. Target group-specific didactics should also include the promotion of self-efficacy expectations, especially for groups that are underrepresented or unsure of how to use AI. By specifically considering the needs and experience gaps identified in the study, the development of AI Future Skills can be sustainably supported by tailoring learning opportunities to the respective target group in terms of both content and methodology.



10

10. Recommendations for action

Considering rapid technological developments and the increasing digitalization of the world of work, it is crucial that education systems and labor markets not only keep pace but also proactively promote the skills and abilities that will be needed in the future. These so-called Future Skills encompass a broad range of knowledge, skills, and attitudes required to succeed in a society characterized by artificial intelligence (AI) and other advanced technologies.

The need to identify, promote, and recognize these skills poses major challenges for educational institutions, companies, and political decision-makers.

The following recommendations for action aim to provide a strategic framework to meet these challenges. They include the need for further research on Future Skills, the development and establishment of target group-specific competence models, the operationalization of Future Skills for individual learning pathways, and the development of specific certification concepts and methods for teaching and testing these skills in various educational sectors. These recommendations serve as guidelines for stakeholders from education, industry, and politics to jointly lay the foundations for a future-proof society in which every individual can acquire and further develop the skills required for the 21st century.

1. more research on Future Skills

- Initiate interdisciplinary research projects: Establish research consortia that include industry, educational institutions, and government agencies to identify and analyze evolving Future Skills.
- Long-term studies: Conduct long-term studies to understand the evolution of Future Skills over time and forecast the impact of technology on the labor market.

2. establishment of further competence models

- Target group-specific skills analyses: Development and implementation of detailed skills models for specific target groups, e.g. industry experts, to determine precise skills requirements.
- Participatory approaches: Involve stakeholders from different sectors in the development of the skills models to ensure their relevance and applicability.

3. operationalization of Future Skills models

- Development of learning paths: Creation of individual learning pathways based on the Future Skills models to provide personalized training and qualification opportunities.
- Integration into existing training platforms: Adaptation and integration of the Future Skills models into existing online learning platforms and management systems.

4. development of specific certification concepts

- Implementation of micro-credentials: Development of certification concepts, such as open badges and micro-credentials, which facilitate the recognition of Future Skills.
- Partnerships with industry and accreditation bodies: Work with industry and official accreditation bodies to increase the credibility and acceptance of certifications.

5. development of methods for teaching and testing Future Skills

- Innovative teaching methods: Use and promotion of innovative teaching and learning methods aimed at teaching Future Skills, including project-based learning approaches and digital simulations.
- Development of examination standards: Development of standards and guidelines for the assessment of Future Skills to ensure consistent and fair assessment.

6. development of Future Skills models for different education sectors

- Sector-specific models: Developing and adapting Future Skills models for different education sectors, including schools, higher education, and vocational education and training, to meet their respective needs.

- Intersectoral cooperation: Promote cooperation between education sectors to enable the exchange of best practices and support the development of transversal competences.

7. policy measures

- Strengthening AI education initiatives: The government should specifically promote programs and initiatives that focus on AI education and training. This includes the development and provision of teaching and learning materials specifically aimed at imparting knowledge about AI technologies and their application.
- Financial support and resource provision: Financial incentives should be provided to organizations and individuals to promote the development of AI skills. This includes scholarships, research grants, and access to necessary technologies and infrastructures to enable learners and researchers to actively engage with AI.

8th AI Campus Initiative

- Development of a comprehensive AI strategy: A coherent strategy should be developed that includes educational offers, training opportunities, research activities, and political support mechanisms. This strategy should aim to create an ecosystem that promotes exchange between educational institutions, companies, research institutions, and political decision-makers.
- Platforms for exchange and networking: The creation of online and offline platforms that facilitate exchange and networking between all actors in the field of AI education is essential. These platforms can help share best practices, foster collaborations and build a community that works together to promote and develop AI skills.
- Practice-oriented learning opportunities and ethics of AI: Particular attention should be paid to the development of practice-oriented learning opportunities that enable learners to work on real-world problems with AI solutions. It is also important to place a strong focus on ethical considerations when dealing with AI in all educational offerings. This includes addressing issues of data protection, fairness, transparency, and responsibility when using AI technologies.

These recommendations for action provide a framework for systematically and sustainably promoting the development and dissemination of AI skills. They encourage collaboration between the various sectors and aim to shape an inclusive, ethically sound, and technologically advanced future.

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Attachments

11. Attachments

Questionnaire of the AIComp study----------

Artificial intelligence in everyday working life -
What skills do you need to deal with it?

Welcome to our survey!
Artificial intelligence (AI) is dominating headlines and conversations - and not just since ChatGPT & Co. became available to everyone. Have you had anything to do with it? How well prepared do you feel for the topic of AI in your day-to-day work? We would be delighted if you could take around 15 minutes to complete the questionnaire!

Who is behind it?
The survey is being carried out by the Baden-Wuerttemberg Cooperative State University together with the Karlsruhe Chamber of Industry and Commerce, the Heilbronn Chamber of Industry and Commerce and Südwestmetall. The survey is funded by the Federal Ministry of Education and Research (BMBF) and the Dieter Schwarz Foundation via the "KI-Campus" and "KI-Hub BaWü" initiatives. The "KI-Campus" is the German-language learning platform for anyone who wants to strengthen their AI and data skills - with free learning modules (more information at www.ki-campus.org). In addition to the DHBW, other renowned universities and research partners are also involved.

Help us to create better conditions for further education in the field of AI!
This questionnaire is about AI. What does it mean?
Artificial intelligence (AI) refers to special computer programs that can independently learn new things and make decisions on their own in complex situations. They are often able to perform tasks that come close to human intelligence. In many places, computers are already using such AI components in the background without non-experts noticing.
In this study, we are asking for your experiences and assessments of AI applications. Examples include ChatGPT or similar applications, the translation program DeepL, image-generating AI, but also smart home devices, etc.).

Part 1: Your experiences and attitudes towards AI
In the first part, we are interested in how you rate your own experience of using AI and what you think of AI in general.

Q1. How would you rate your own use of AI applications? Please select the answer option that applies most to you.

Table 1

Q1-1 Passive use: I use AI systems passively without actively adapting them.	(1)
Q1-2 Active use: I understand the basic functioning of AI systems and use them actively in my daily work.	(2)

Q1-3 Co-creation and development: I actively participate in the introduction and development of AI systems and can identify new possible applications.	(3)
Q1.4 I have not yet used any AI systems.	(9)

Q2. Do you use AI applications in your professional and/or private life?

Table 2

	in the professional sphere i	in the private sphere	neither
	(1)	(2)	(9)

Q3. How often do you use AI applications?

Table 3

	Not at all so far	several times already	regularly: about once a week	Very often: several times a week
	1	2	3	4

Note: If you have not yet used AI applications at all, we would like to encourage you to complete the questionnaire anyway and let us know your opinion on the other questions. If you do not wish to do so, you can complete the questionnaire here <LINK to end>. We would like to take this opportunity to thank you for your cooperation!

Q4. AI applications have recently become accessible to many users. We are interested in your opinion on the following statements. Please indicate the extent to which you agree with each:

Table 4

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q4-1 I assess the use of AI in my area of work positively.	4	3	2	1	9
Q4-2 I think it is likely that AI will influence my work tasks in the near future.	4	3	2	1	9
Q4_5 I think it is good that AI influences important decisions in personal areas of life such as health, education and finances.	4	3	2	1	9
Q4_4 In my opinion, AI will lead to job losses in the future.	4	3	2	1	9

Q4-3 I believe that AI will eventually be superior to human intelligence.	4	3	2	1	9

Part 2: Your skills in dealing with AI

The next part is about 12 skills that are useful when dealing with AI. For each of these skills, there are now three statements for which we would like your assessment:

1. the first one is about whether you have already gained experience with AI in this respect.
2. in the second, we ask how confident you feel with the skill.
3. the third is about your assessment of how important this capability will be in the future.

Q5. Using AI for decision-making (e.g. via search engine recommendation systems, voice recognition such as Siri or Alexa, social media analysis systems or Linked-In)

First of all, we are interested in the ability to use AI for decision support. Please mark which answer option is most likely to apply to you.

Table 5

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q5-1 I often use AI in my field of work to support decision-making (e.g. stock trading, travel planning).	4	3	2	1	9
Q5-2 I feel comfortable getting advice from an AI assistant at work.	4	3	2	1	9
Q5-3 In my view, the ability to use AI systems for decision support will become increasingly important in the future.	4	3	2	1	9

Q6. Further training on AI

How do you feel about continuing your education on the subject of AI? Below you will find three statements on this topic.

Table 6

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q6-1 I have undergone further training on the topic of AI in the last 12 months (e.g. training on how to use AI tools or AI applications).	4	3	2	1	9
Q6-2 I am confident that I can keep up with new developments in the field of AI through learning/ further training.	4	3	2	1	9

Q6-3 I am convinced that continuous training on the subject of AI will be an important factor for future professional success.	4	3	2	1	9

Q7. Critical thinking in relation to AI

Now it is about the ability to critically assess AI and information generated by AI. Please indicate the extent to which you agree or agree with the following statements.

Table 7

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q7-1 I have a lot of experience in critically reviewing AI-generated information (e.g. with fact-checking or additional research).	4	3	2	1	9
Q7-2 I feel competent to judge up to what point AI-generated information is useful to me and when it is no longer useful.	4	3	2	1	9
Q7-3 The ability to critically question AI systems is becoming increasingly important in my field of work.	4	3	2	1	9

Q8. Ethical aspects of AI

The following deals with ethical aspects of the application and use of AI, e.g. in relation to built-in discrimination or possible job loss through automation. Ethical awareness is expressed, for example, in a reflective attitude or a critical awareness of an issue.

Table 8

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q8-1 I have already dealt intensively with ethical questions about the use of AI systems (e.g. because of built-in discrimination or other issues).	4	3	2	1	9
Q8-2 I feel comfortable raising ethical concerns related to AI (e.g. because of built-in discrimination or possible job loss due to automation).	4	3	2	1	9

Q8-3 In my view, the importance of ethical awareness in relation to AI will increase significantly in the future.	4	3	2	1	9

Q9 Self-determination in the use of AI

We are now interested in the ability to confidently distinguish between human and artificial intelligence and to use it according to your own ideas. Please indicate to what extent you agree or agree with the following statements.

Table 9

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q9-1 I have experience in adapting AI-based suggestion systems so that they do not confront me with things I do not want to see or hear.	4	3	2	1	9
Q9-2 I trust myself to use AI technologies in a way that supports me but does not patronize me.	4	3	2	1	9
Q9-3 In the future, it will be difficult to recognize the transition between self-determination and heteronomy through AI systems.	4	3	2	1	9

Q10. Using AI as a tool

Now to the ability to use AI as a tool. Please indicate to what extent you agree or agree with the following statements.

Table 10

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q10-1 I use AI applications as a tool to complete my tasks.	4	3	2	1	9
Q10-2 I am confident that I can actively integrate AI tools into my own work process.	4	3	2	1	9
Q10-3 AI applications will play a decisive role in my field of work in the future.	4	3	2	1	9

Q11. Understanding AI as a system

AI applications often combine complex AI systems with each other (e.g. chatbots, financial trading systems, autonomous vehicles) without these always being immediately recognizable. Do you know

the logic behind AI systems? This is the subject of the next block of questions. To what extent do you agree with the statements?

Table 11

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q11-1 When using AI systems, it is always important for me to understand the logic behind the AI system.	4	3	2	1	9
Q11-2 My understanding of how AI systems work allows me to use AI applications that are new to me with confidence.	4	3	2	1	9
Q11-3 In my view, AI can only be mastered in the future if all employees have a deep understanding of the underlying systems.	4	3	2	1	9

Q12. Co-designing AI systems (e.g. personalization of recommendations, user-defined filtering of content, adaptation of auto-correction, etc.)
The ability to actively help shape AI applications or systems is interesting for us. How do you feel about this?

Table 12

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q12-1 I have already imagined how I could use AI systems for my own field of work in the future.	4	3	2	1	9
Q12-2 I feel comfortable helping to shape the future use of AI technologies in my professional environment.	4	3	2	1	9
Q12-3 The ability to actively shape the use of AI systems in my field of work will be important for my professional success in the future.	4	3	2	1	9

Q13. support creativity with AI (e.g. generation of ideas, AI-supported image and text creation, AI-supported creativity tools, etc.)

Can you use AI to improve your creativity - and does AI lead to more innovation? This is the subject of the following block of questions.

Table 13

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q13-1 I have experience in using AI-based solutions to develop ideas for creative solutions to problems (e.g. creative generation of images with an AI application).	4	3	2	1	9
Q13-2 I am confident in using targeted questions ("prompts") to elicit better suggestions and ideas from text AI systems and image AI systems.	4	3	2	1	9
Q13-3 The ability to use AI systems to develop creative ideas will become more important in every field of activity in the future.	4	3	2	1	9

Q14. Take initiative with regard to AI
How proactively do you take on the topic of AI? Please indicate the extent to which you agree or agree with the following statements.

Table 14

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q14-1 I have already suggested the use of AI applications in my field of activity.	4	3	2	1	9
Q14-2 I am confident that I can take the initiative when it comes to introducing AI systems in my field of work.	4	3	2	1	9
Q14-3 In my opinion, it will be important for professional success in the future to take the initiative when it comes to using AI.	4	3	2	1	9

Q15 Collaboration on the topic of AI (cooperation with AI systems such as chatbots or for data analysis, but also cooperation with colleagues in AI projects)
Do you feel well equipped to work effectively with AI systems and other people to achieve common goals? This is the subject of the following block of questions. Please also indicate here to what extent you agree with the following statements or find them applicable.

Table 15

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q15-1 I have had experience of working with others on AI projects or plans.	4	3	2	1	9
Q15-2 I feel well equipped to collaborate on AI projects with experts from other fields.	4	3	2	1	9
Q15-3 The ability to collaborate with others on AI topics across disciplines will be essential for my professional success in the future.	4	3	2	1	9

Q16 Communication on the topic of AI
The ability to communicate with others about AI systems and related topics is often not easy. How do you see this? Please indicate the extent to which you agree or agree with the following statements.

Table 16

	Fully applies	Applies	Does not apply	Does not apply at all	Cannot judge
Q16-1 I have already exchanged views on AI topics with colleagues or acquaintances.	4	3	2	1	9
Q16-2 I feel confident in communicating with others who have different views on AI topics.	4	3	2	1	9
Q16-3 In my field of work, communication skills on the topic of AI will be particularly important in the future.	4	3	2	1	9

Q17 Thank you very much so far! Would you like to add any other important skills for dealing with AI in everyday working life? Then you have the opportunity to do so here. Simply enter them in the following field: (freetext)

Q099 - We have formulated some separate questions for dual partner organizations of the DHBW. Therefore, please indicate here whether your organization is a dual partner of the DHBW. (Scale: Yes - No - I don't know)

Filter questions for dual partners
<Filter: For all those who have indicated "YES" for Q099, please show the following questions

Q100 - In your opinion, how prepared are DHBW students currently for dealing with AI? (Scale: very good - good - sufficient - not sufficient - I cannot judge)
Q101 - What would you like to see more of from the DHBW on the subject of AI in the future (multiple choice)
- Special AI study programs
- Special AI supplementary courses
- Use AI tools in teaching (e.g. chatbots)
- University should offer us advice on the topic of AI
- University should offer us further training on the topic of AI
- Joint research initiatives on the topic of AI
- Other: (freetext)
Q102 - Thinking about your company / organization: How important do you think it is to build up expertise in AI in the future?
- Today: very important (4) - important - unimportant - not important at all (1) - I can't say (9)
- In 3 years: very important (4) - important - unimportant - not important at all (1) - I cannot judge (9)
Q103 - In which areas of your organization do you currently use AI?
- (freetext)
Q104 - In which areas do you plan to use AI within the next 2 years?
- (freetext)

Questionnaire part 3: Social statistics
In the last part of the survey, we ask you to provide statistical information about yourself, the organization to which you belong and your professional situation. Please enter the data in the relevant answer fields or mark the answer option that best applies to you.

Q18 Year of birth (free entry, 4 digits)
Please enter your year of birth.

Q19. gender (as dropdown selection: M / W / D / not specified)
Please state your gender.

Q20. professional position (selection: list)
Please select a professional position from the list that best applies to you.
(1)Managing director
(2)Manager
(3)Project manager
(4)Team leader
(5)Sales representative
(6)Marketing employee
(7)Financial analyst
(8)Personnel officer
(9)Customer service representative
(10) IT specialist
(11) Software developer
(12) Data analyst
(13) Researcher
(14) Lecturer
(15) Teacher
(16) Engineer

(17) Designer
(18) Accountant
(19) Lawyer
(20) Service employee
(21) Administrative assistant
(22) Logistics employee
(23) Medical doctor
(24) Other: Please indicate your professional position in the industry.

Q21 Size of the organization (enter number field)
How large is the organization to which you feel you belong? Please enter the total number of employees.

Q22. industry (selection: list)
In which industry do you work?
(1) Activities in management & consulting
(2) Activities in the areas of business operations and finance
(3) Activities in the fields of IT and mathematics
(4) Activities in the fields of architecture and engineering
(5) University and science activities
(6) Legal activities
(7) Education, training and library activities
(8) Activities in the fields of art, design, entertainment, sport and media
(9) Medical professionals and specialist activities
(10) Healthcare workers
(11) Activities in the fields of protection and security
(12) Activities in the areas of food preparation and catering
(13) Activities in the areas of building and property cleaning and maintenance
(14) Activities in the fields of personal care and wellness services
(15) Sales and related activities
(16) Office and administrative support activities
(17) Activities in agriculture, fishing or forestry
(18) Construction and extraction activities
(19) Installation, maintenance and repair activities
(20) Activities in production
(21) Activities in the fields of transportation and logistics
(22) Other (please specify)

Thank you very much for your participation and support. You have helped us a lot!