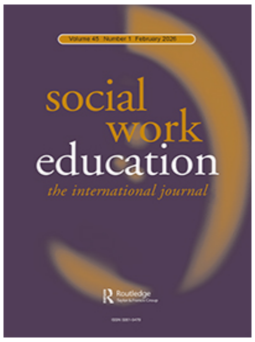

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Promoting AI literacy in social work education: lessons from an interdisciplinary course for social work students

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ABSTRACT

Artificial intelligence (AI), particularly generative AI and large language models (LLMs), are reshaping the landscape of social work practice. Schools of social work are only beginning to respond to these changes. This article presents findings from an interdisciplinary summer school course designed to promote AI literacy among social work students. The curriculum combined a range of interactive learning experiences with time for ethical reflection, and a developmental experience of creating domain-specific CustomGPTs. In order to understand student's acquisition of AI knowledge and skills, we used an AI literacy measure called the *'Scale for the assessment of non-experts' AI literacy'* (SNAIL). We assessed changes in AI literacy through pre- and post-course self-assessments based on the SNAIL questionnaire. The results show statistically significant and potentially meaningful gains in AI literacy. The responses suggest that the course helped increase AI knowledge, enabling students to shift from hesitant observers to confident users of and thinkers about AI tools. This study contributes to the emerging field of AI literacy in social work by offering a model for interdisciplinary teaching on generative AI content.

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AI literacy; digital literacy; prompt engineering, CustomGPT; generative AI; learning outcomes; social work education

Introduction

Social work education has been slow to integrate content and skill development on digital competence, including data and artificial intelligence literacy. Yet, social work is committed to a person-in-environment perspective. Simultaneously, AI is impacting the individuals, organizations and communities that social work cares most about. A recent literature review by Garkisch and Goldkind (2025) utilizes Staub-Bernasconi's triple mandate model to illustrate the effects of AI at all levels of social work practice.

While AI development has been evolving since the 1960s, the release of generative AI tools and Large Language Models (LLMs) has significantly increased the interest in AI literacy in social work. Furthermore, '[p]ractitioners in a variety of professions, including social work, are rapidly increasing their use of AI' (Reamer, 2023, p. 65).

The deployment of commercial LLMs is newer, but calls for digital literacy in the social work profession are at least twenty years old. Rafferty and Steyaert (2007)

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emphasized the growing role of information and communication technologies (ICT) in daily life, suggesting that curricular changes in social work education were necessary. In light of the rise of LLMs, a similar question now arises: How can schools of social work equip students with critical digital literacy skills?

To foster the needed development of AI-related competencies for social work students, we organized a summer school focusing on AI and social work. In order to understand the social work student's acquisition of AI knowledge and skills, the SNAIL assessment was used. Here we present the findings of this survey and recommendations for promoting AI literacy in social work education.

Digital literacy & social work

As digitalization advances, it is becoming increasingly important for social workers to possess the necessary skills to drive the digital transformation of their profession (Weber & Rink, 2025). However, the literature suggests that the needed knowledge is still limited (e.g. Heinsch et al., 2025; Zemaitaityte et al., 2024; Zhu & Andersen, 2021). While early efforts to bridge this gap focused on communication tools and informatics, such as e-mail, data management and stewardship; more recent scholarship has expanded to include newer technological developments, such as social media, machine learning, and, most recently, generative artificial intelligence.

Calls for digital literacy

Social workers 'have a long history in technology avoidance' (Granholm, 2016, p. 33; see also Goldkind et al., 2016). Part of this resistance may stem from the profession's human-centered ethos, which positions interpersonal connection at its core: 'Social work is about people,' as Watling and Rogers (2012, p. 72) note, 'and it is likely to have been the social aspect which called you, rather than any desire to work with computers or develop your digital literacies.' This tension is further amplified by longstanding concerns that digital systems may privilege standardization at the expense of case-specific, situational judgment (e.g. French & Stillman, 2014).

Internationally, social work scholars have recommended the infusion of content on information and communication tools (ICT) into the social work curricula in order to build the knowledge and skills to engage meaningfully in a digital society. From the calls for a social work informatics (Gillingham, 2014; Naccarato, 2010), suggestions for including data justice in the social work education curricula (Goldkind et al., 2021), or a more broad demand for competence in digital literacy (Kilpeläinen & Päykkönen, 2014; McInroy, 2019; López Peláez et al., 2017). These demands are related to technological advances. In the 1990s, scholars began to emphasize that digital competencies, particularly the ability to use emerging technologies for communication, were becoming essential for professional education and practice (Finn, 1996). With further advances in informatics and data processing, Parker-Oliver and Demiris (2006) emphasized the need to train practitioners 'on the use of these emerging technologies and on their possible benefits to practice settings' (p. 131).

Moving into the 21st century, digital technologies play a crucial role in everyday life, where digital media can be seen as 'one of the main *obsessions* of our time' (Balbi &

Magaudda, 2018, p. 6). In addition, the growing datafication in our society means that data literacy has become a practical need in social work (Perron et al., 2022). Most recently, suggestions have been made for engaging with more proliferated large language models and generative AI. These include adding an accreditation standard to social work curricula in the USA (Rodriguez et al., 2024), suggestions for infusing AI literacy into existing accreditation standards (Ahn et al., 2025) and expanding research efforts to understand the implications of large language models for social work education and practice (Báez et al., 2025).

AI specific literacy needs

In general, AI literacy refers to the set of knowledge, skills, and dispositions that enable individuals to engage with AI in informed, responsible, and critical ways. Building on the well-refered model proposed by Long and Magerko (2020), AI literacy includes understanding what AI is, what it can do, how it works, how it should be used, and how it is perceived by society. In the context of social work, Ahn et al. (2025) emphasize that this framework provides a foundational basis to 'help social workers navigate AI's dual role in exacerbating inequalities and creating opportunities for advancing practice' (p. 18). A recent systematic review by Almatrafi et al. (2024) examined 47 papers on AI literacy published between 2019 and 2023. The review identified six core constructs of AI literacy that are central to current discourse.

(1) Recognize: being able to identify AI-driven technologies and distinguish them from non-AI systems;
(2) Know and Understand: acquiring foundational knowledge of AI concepts and techniques;
(3) Use and Apply: developing the ability to meaningfully interact with AI systems;
(4) Evaluate: critically assessing the capabilities, limitations, and impacts of AI tools;
(5) Create: the ability to design or program AI applications (though not always essential for non-technical users);
(6) Navigate Ethically: understanding the societal and ethical implications of AI use, including bias, accountability, and fairness.

Taken together, these frameworks define AI literacy as a cross-cutting competence that is highly relevant for social work education to prepare students for a future 'Artificial Intelligence Enhanced Social Work' (Garkisch & Goldkind, 2025, p. 23).

Toward addressing the gap: an interdisciplinary course on social work and AI

In order to prepare social work students for their future professional practice characterized by AI, the 2025 Summer School at the FHNW School of Social Work was designed on the topic of AI. Under the title 'Social Bytes and Artificial Minds: Digitalization and Artificial Intelligence—Opportunities, Challenges and Implications for Social Work,' we spent the first week of June 2025 at the Muttenz campus exploring the current state of technological AI developments and their social impact. The topic was addressed over the course of five days through different formats and levels of engagement. During the course, for example, students engaged with AI through lectures, interactive formats, explored applications in social work via workshops, and critically examined the social and ethical implications of AI technologies. A central component was the development of domain-specific CustomGPTs, guided by computer science facilitators and informed by inputs on LLMs. Further details on the scope of the CustomGPTs and our teaching experience from a Requirements Engineering perspective can be found in Fricker et al. (2025). The program concluded with student presentations of the chatbots that they had developed. Appendix A includes a detailed course description.

Methods

In order to understand the learning outcomes of the participants in this summer school, we used pre- and post-course surveys with open-ended questions, overall ratings and the SNAIL assessment to assess changes in AI literacy.

Sample

A total of 28 students participated in the course, the majority of whom were undergraduate or graduate students in social work. Two participants had a background in accounting. All participants were over the age of 18 years old. Students ranged in age from 20 to 49. They represented three countries, including five students from Germany and three students from France. Three schools of social work and one business school participated in the course, with the majority of students coming from the host school.

Measures

To assess the learning outcomes of the summer school, we administered self-assessment surveys at two points in time. Approximately two weeks before the summer school began, students were invited by e-mail to complete an online pre-survey; the corresponding post-survey was conducted on-site at the end of the course. The aim was to capture changes in participants' perceived AI literacy. Both surveys were created and distributed using the EFS survey platform (Tivian). To enable matching of individual pre- and post-responses while preserving anonymity, participants generated personal codes.

The main instrument used in both surveys was the Scale for the Assessment of Non-Experts' AI Literacy (SNAIL),[1] developed by Laupichler et al. (2023a, 2023c).[2] It is designed to assess the AI literacy of non-technical publics, to evaluate the effectiveness of AI literacy training programs (Laupichler et al., 2023a), such as the summer school.

The scale was developed to expand the existing landscape of AI literacy assessment. The goal was to create a questionnaire specifically tailored for non-experts, which include AI-specific items that are not conflated with general digital literacy. The authors took a 'bottom-up research approach by moving from specific items to generalized latent factors' (Laupichler et al., 2023a, p. 2). To generate the initial AI literacy item set, they conducted a Delphi expert study (Laupichler et al., 2023c). This was necessary due to the still limited and fragmentary theoretical foundation of AI literacy. An exploratory factor analysis was then carried out on this initial set of items to develop the SNAIL questionnaire. First empirical evidence suggests that the items can reliably and validly assess non-experts' AI competence. The resulting instrument comprises 31 items, which load onto three overarching factors, conceptualized as the TUCAPA model of AI literacy. This model includes the dimensions *Technical Understanding*, *Critical Appraisal*, and *Practical Application* (Laupichler et al., 2023c). The items that make up the SNAIL questionnaire are shown in Appendix B.

While the items in our surveys were displayed in randomized order to avoid response bias, the students rated their competencies for each item on a scale from 1 (strongly agree) to 7 (strongly disagree).

Analysis strategy

Following the method described by Laupichler et al. (2023b), a one-tailed paired-samples t-test was used to analyze[3] the learning progress in the three factors of *Technical Understanding*, *Critical Appraisal*, and *Practical Application* before and after the course. Pre-course ratings were compared with post-course ratings from the same participants. The one-tailed test was justified by the directional hypothesis that students' competencies in these factors would improve throughout the course. Due to the varying initial levels of students prior to the course, the actual increase in self-reported competence alone is not fully adequate for evaluating learning outcomes. Therefore, 'a comparison of performance levels of individual students before and after course participation' (Laupichler et al., 2023b; Raupach et al., 2011, p. 447) is necessary, as it takes into account the difficulty of further increasing skills, knowledge, and attitudes in more advanced students. Therefore, following the t-test, we calculated factor-specific gains using the Comparative Self-Assessment (CSA) method. The CSA does not measure absolute improvement, but rather the percentage gain relative to the maximum possible individual improvement. The CSA is defined as (Raupach et al., 2011):

$$CSAgain(\%) = \frac{\mu_{pre} - \mu_{post}}{\mu_{pre} - 1} \times 100$$

This yields values from −100% to +100%, where, for instance, a shift from 5.0 to 3.0 reflects the same gain as a shift from 2.0 to 1.5, since both represent 50% of the potential improvement from the initial level (Raupach et al., 2011).

Findings

The following section presents the results obtained from the pre- and post-surveys. First, we explore students' perspectives on AI before the course, illustrating how AI is currently utilized and perceived in academic, professional and personal contexts. Next, we present evidence of substantial improvements in AI literacy, as measured across technical, critical, and practical dimensions using the SNAIL questionnaire. This demonstrates how students developed a sense of empowerment, critical reflection, and ethical awareness. Finally, we report on participants' overall experience of the summer school, which they rated highly. Overall, the results emphasize the potential of interdisciplinary, intensive and hands-on learning formats to enhance the AI literacy of social work students.

Pre-course perspectives on artificial intelligence

In addition to the SNAIL-questionnaire, we asked students open-ended questions about their perception and actual usage of AI in the pre-course survey. To analyze this data, we applied a qualitative content analysis, as we were interested in the latent content. The reported results rely on 24 responses.

Students reported using AI primarily as a versatile support tool in academic and personal contexts. They use AI to summarize content, paraphrase, generate ideas, structure written work, prepare presentations and improve language and grammar. Few students also use AI for coding support and data analysis. Also, students rely on AI for tasks such as composing e-mails, translating texts, generating recipes, managing tasks and seeking quick explanations. A few students mentioned using AI for creative purposes, such as creating artwork and social media posts. While one student reported not using AI at all, the overall picture reflects its broad and growing integration into intellectual, organizational and creative tasks.

When asked about the meaning of AI, students described it as a multifunctional, supportive tool that assists with daily tasks, academic study and professional work. Many students view AI as a means to enhance efficiency in different areas such as research, writing, problem solving and learning, describing it metaphorically as a 'second, more functional brain' or an 'intelligent form of search engine.' However, several students emphasize the importance of critical evaluation and caution against overreliance on AI, stressing that human judgment remains important. Alongside utilitarian perspectives, some responses demonstrate a deeper ethical and philosophical interest, particularly with regard to inclusion, responsibility, and embodiment. While some students still feel unfamiliar or uneasy about AI ('I don't know yet—it scares and intrigues me'), they recognize its potential.

In order to understand how students keep up to date with AI, we asked them where they learn about AI resources and tools. The responses show that social environments and informal digital channels play an important role. Students reported discovering new tools on social media platforms such as TikTok, Instagram, LinkedIn or YouTube, or by talking to friends, classmates or family members. As one student puts: 'I usually learn about new AI tools through social media—especially TikTok and Instagram, where people often share quick demos or tips.' Others mentioned university courses or specific events at their institution. One participant described their experience as 'learning by doing,' emphasizing that much of their AI usage had come from hands-on experimentation rather than formal instruction. The answers indicate that, in addition to formal education, peer exchange, digital content and personal exploration are significant sources for acquiring AI knowledge.

To explore students' expectations regarding the impact of AI on their future profession, we asked them how they thought AI tools would affect social work. The responses reflect a pragmatic yet cautious optimism. Students expect AI to be a valuable support tool, particularly for administrative and repetitive tasks such as writing reports, managing documentation and scheduling. As one student noted, 'AI tools could really help social work by saving time on repetitive tasks, like writing reports or managing files, so that social workers can focus more on helping people.' Similarly, others suggested that AI could enhance efficiency, assist with case analysis and improve access to services, particularly in intercultural contexts. However, many respondents also emphasized the irreplaceable value of human interaction. Empathy or ethical judgment were cited as qualities that AI cannot replicate. One student warned in a dystopian manner, that 'AI will decide who will get services; first responder call centers will go AI; with AI the gov can analyze the whole lifestyle of a person and cut services accordingly.' Concerns also emerged regarding data protection, the risk of over-standardization and inequitable access. Overall, students view AI as a means of streamlining bureaucratic tasks and freeing up time for client-focused work. However, they emphasize again that social work must remain grounded in human relationships and critical oversight.

AI literacy gains during the course

Students demonstrated statistically significant improvements in all dimensions of AI literacy assessed by the SNAIL questionnaire from pre- to post-course self-assessment. These gains were consistent across the conceptual, applied, and critical components of AI literacy, as defined by the TUCAPA model. Out of the 28 students who participated in the course, 17 provided responses to both the pre- and post-surveys.

In the *Technical Understanding* dimension, the mean score decreased from 5.39 (SD = 0.95) before the course to 3.13 (SD = 0.99) after the course, $t(16) = 8.54$, $p < .001$. This decline indicates a substantial improvement in participants' perceived understanding of fundamental AI concepts and mechanisms. The effect size was very large (Cohen's $d = 2.07$), indicating a strong educational impact. However, the correlation between pre- and post-scores was relatively low ($r = .37$, $p = .07$), suggesting notable individual variation in the degree of conceptual learning achieved. In the *Practical Application* category, students' self-assessments improved from a mean of 4.04 (SD = 1.18) to 2.34 (SD = 0.89), $t(16) = 8.26$, $p < .001$. This indicates a marked increase in participants' confidence in using AI tools in practice. The effect size was again very large (Cohen's $d = 2.00$), and the strong correlation between pre- and post-scores ($r = 0.70$, $p = 0.002$) points to relatively consistent progress across the cohort in this area. In the *Critical Appraisal* dimension, which assesses the ability to reflect on the implications, risks, and ethical considerations of AI, the mean score decreased from 3.75 (SD = 1.18) to 2.21 (SD = 0.84), $t(16) = 7.83$, $p < .001$. The corresponding effect size (Cohen's $d = 1.90$) again reflects a very strong effect, and the high correlation between pre- and post-scores ($r = .72$, $p = .001$) suggests that most students developed critical perspectives on AI to a similar extent.

The pre—post differences in self-assessed AI literacy across all three dimensions are illustrated in Figure 1.

As previously mentioned, differences in students' prior knowledge levels should be considered when interpreting learning outcomes. The Comparative Self-Assessment (CSA) method addresses this by normalizing individual gains relative to the maximum possible improvement. An item-level analysis of CSA gains (see Figure 2) reveals notable variation in perceived learning across the different aspects of AI literacy. Items with lower CSA gains can often be explained by the limited or absent coverage of those topics during the summer school. For instance, the item 'I can explain how sensors are used by computers to collect data that can be used for AI purposes' showed relatively low improvement, likely because this specific aspect was not explicitly addressed in the course. In unsurprisingly contrast, items with high

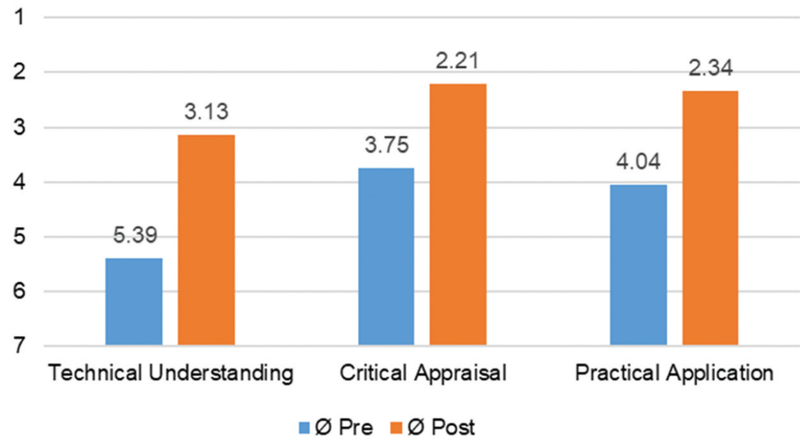

Figure 1. Gains in AI literacy across TUCAPA.

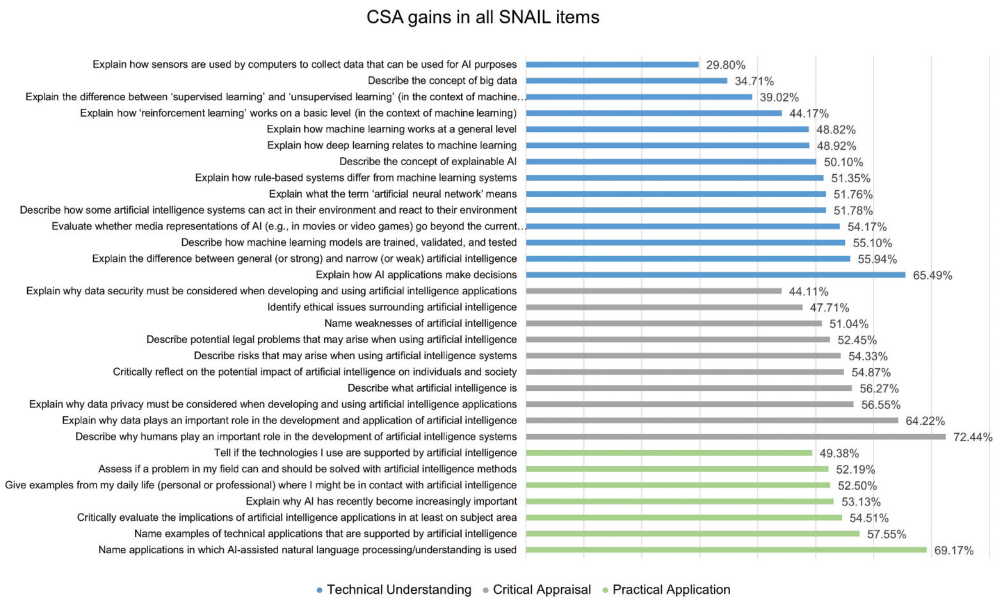

Figure 2. CSA gains in SNAIL items.

CSA gains often corresponded to explicitly covered topics, such as the role of humans in AI development, which was discussed in multiple sessions. Overall, the factor-specific analysis of CSA gains confirms substantial progress in perceived learning across all dimensions of AI literacy. With regard to the three TUCAPA factors, participants achieved on average a 51.0% gain in *Technical Understanding*, 58.3% in *Critical Appraisal* as well as in *Practical Application*. These values indicate that, on average, students achieved more than half of the maximum possible self-assessed improvement.

Taken together, these findings provide evidence that the summer school was effective in increasing students' AI literacy. The statistically significant mean differences and consistently large effect sizes across all factors supports the conclusion that participants not only acquired new knowledge but also developed greater confidence in applying AI tools and critically engaging with their implications. These results underscore the value of interdisciplinary training formats for equipping students with the multifaceted competencies required to navigate AI in social work contexts.

Participants overall experience

In the post-survey questionnaire, we asked students to rate their summer school experience across different dimensions using a five-point Likert scale ranging from 'strongly agree' to 'strongly disagree.' The results from the 21 responses we received in post-survey are shown in Figure 3.[4]

The results indicate a high level of overall satisfaction with the summer school. A total of about 86% of participants either agreed or strongly agreed that they were satisfied with their overall experience. Similarly, 76% of participants found the topics to be relevant and well-structured, and 76% felt that the level of content was appropriate for their background. Notably, 91% (strongly) agreed that they would recommend the summer school to others.

These results suggest that the summer school met the expectations of most participants and delivered content that was both suitable and relevant. The high recommendation rate further underscores the programme's perceived value and impact. The absence of strong disagreement in all categories indicates a generally positive reception and low levels of dissatisfaction.

In future iterations, closer attention should be paid to ensuring that the entry level and corresponding content level are appropriate for all participants.

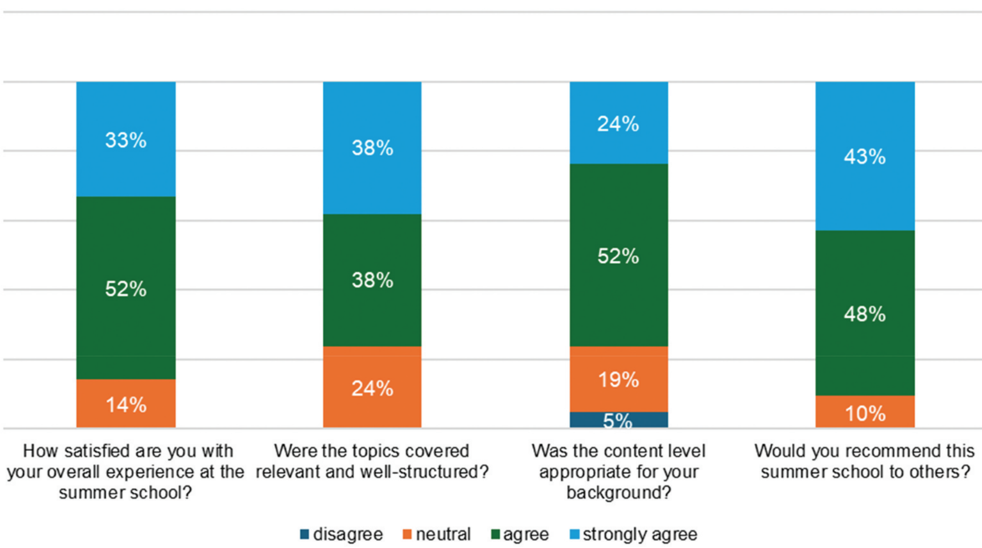

Figure 3. Participant feedback on summer school experience.

Discussion

The international community of social work educators recognizes the need for schools of social work to prepare students for practice with artificial intelligence (Goldkind, 2021; O'Leary & Tsui, 2023). An allied, longer standing aspiration is to prepare students for interdisciplinary practice settings (Grossman & McCormick, 2003; Miller et al., 2019). This course sought to address both of these needs. Curricula in social work education generally includes content on social work skill development, social work content knowledge and acculturation to social work values (Bracy, 2017). These dimensions are also articulated by the International Federation of Social Work's *Global Standards for Social Work Education and Training*, which focuses on 'social work in context' and 'social work in practice' (International Federation of Social Workers [IFSW], 2020). With few exceptions, schools of social work have not included the digital arena as a social work context nor an area of social work practice. Programs such as the e-social work degree at the University of Lapland which operated from 2008 to 2011 offered a dual masters degree in social work and information technology.[5] Additional examples include a master's program focusing on social work, research and digitalization, Munich University of Applied Sciences in Germany, as well as the masters in Digitalization in Social Work at Baden-Württemberg Cooperative State University (DHBW) also located in Germany. The European Joint Master's in Social Work with Children and Youth is based on three pillars, one of which is digital social work. Other social work degree programs have offered one-off courses or electives on social work and digital content in their curricula such as the Protestant University of Applied Sciences Freiburg, TH Köln—University of Applied Sciences in Germany, and Columbia University, in the United States. These courses are useful for the limited number of students which will be reached by their content, but as yet, a more comprehensive effort has not been made,[6] even though some countries are including digital content and competency as a mandate.

Digital tools, and AI specifically, are changing social work practice at all levels. Current and future social work students therefore should possess the knowledge and skills to utilize AI tools. Our results suggest that an interdisciplinary course, blending content on the socio-technical elements of AI as well as experiential content on the design and development of generative AI tools offer students a comprehensive learning opportunity. Our preliminary findings indicate that courses taking this approach can be effective in enhancing participants' AI-related competencies across knowledge, skills, and critical-reflective dimensions.

Anecdotally, as we talked to four students after the summer school, they described gaining confidence in using AI tools, particularly through practical engagement with prompt engineering. As one student stated: 'It was an opportunity for me to try it out. And now I feel like, ah yes, now I know a little bit about it, and that's why it's somehow easier for me when I use it for myself now.' Beyond technical skills, student feedback also describes an attitudinal shift. They moved from a passive stance ('AI felt too complex for me') to an active one ('I can design and use AI effectively'). They highlighted moving from initial apprehension to a sense of agency and empowerment. The development of CustomGPTs was experienced as both accessible and meaningful. Offering students time for reflection helped to surface insights on the boundaries of what AI can and should do. One person summarized this tension clearly: 'It should never become your brain or replace your thinking.' AI was not viewed as a replacement for core professional competencies but as a supportive tool whose integration requires critical reflection and professional discernment. The interviews also reflect a growing understanding that social workers have a duty to not only use AI tools skillfully, but also to engage in societal debates about their implications, as one puts: 'There is great potential for social work to become active in cyberspace, as well as a responsibility for social work to have a say in important issues and to promote rights and rules that are currently lacking in the digital world.' Students emphasized the importance of responsible data handling, awareness of AI limitations, and the need for human judgment in client interactions. This anecdotal evidence supports our quantitative measures, that the students did not merely learn how to use AI—they learned how to position themselves in relation to it.

Figure 4 summarizes our approach to the delivery of the course, informed by our findings. We offer this as a starting point for other social work educators interested in replicating a social work and AI course from a socio-technical approach.

(1) *Focus on demystification and empowerment*: Some students entered the course with uncertainty or apprehension about AI. The program successfully helped shift these perceptions by emphasizing accessibility, relevance, and learner agency. Future initiatives should therefore start with low-threshold, non-technical entry points to lower initial barriers and/or offer preparatory self-learning materials to ensure all participants start with a common foundation. To further enhance engagement, programs should foster a sense of ownership through creative and self-directed projects such as building domain-specific GPTs, and highlight non-coding approaches to AI in order to reduce intimidation and make AI literacy feel attainable.

(2) *Combine practical application with critical reflection*: The provided hands-on experience such as creating domain-specific CustomGPTs proved to be

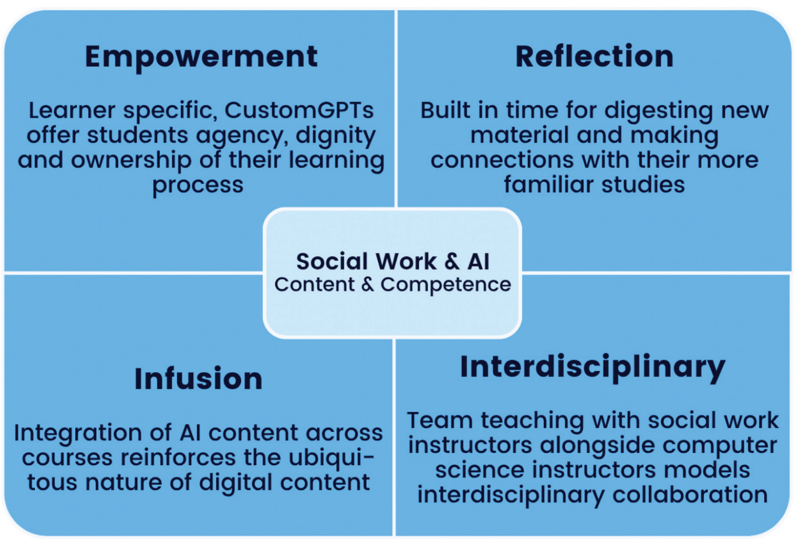

Figure 4. Pillars of AI integration in social work education.

a meaningful way of engaging students and facilitating learning. However, great impact was achieved when this was paired with opportunities for ethical and critical reflection throughout the course. Therefore, future programs should deliberately integrate both. Practice-oriented modules to build confidence and skills, as well as reflective formats such as input sessions followed by discussions or workshops to explore the implications, boundaries and (un)intended consequences of AI in social work.

(3) *Foster interdisciplinary teaching formats to enable multi-perspective learning*: Our summer school demonstrated that AI literacy in social work benefits from interdisciplinary collaboration. This finding aligns with recent curriculum studies that treat AI literacy as a socio-technical competence, requiring collaboration across disciplines (e.g. Tadimalla & Maher, 2024). Bringing together perspectives from social work and computer science helped students to understand AI as both a technical and socio-political phenomenon. This approach not only enriched content knowledge but also supported the development of critical thinking. Future programs should therefore intentionally assemble interdisciplinary teaching teams and learning materials to reflect the multifaceted nature of AI and its implications for social work practice.

(4) *Integrate AI literacy across the curriculum as a cross-cutting competence*: The summer school served as a strong entry point into AI literacy for social work students. To ensure lasting impact, however, such efforts should be embedded more broadly across the curriculum. AI is not a discrete subject but a transversal issue that intersects with many domains of social work and social work education. Embedding AI literacy into multiple modules and levels of study enables students to engage with it repeatedly in diverse contexts, reinforcing both its relevance and their ability to critically reflect on its implications. Achieving this requires more than isolated teaching efforts; it demands an articulated institutional strategy for sustainable integration in HEIs (Deroncele-Acosta et al., 2025, p. 22).

Limitations

Several limitations must be acknowledged when interpreting these results. First, the sample size limits the generalizability of the findings. While the course format—a week-long, focused summer school course—minimized external distractions such as overlapping academic obligations, the number of participants remains too small to draw conclusions beyond this specific context. Moreover, the lack of randomization and a control group means that no causal inferences can be made. Although the observed improvements are statistically significant and align with the qualitative findings, it cannot be conclusively determined that the course alone caused the observed changes in AI literacy. Second, the self-assessment format of the SNAIL survey is susceptible to known response biases. As noted by Caspersen et al. (2017), low-achieving students tend to overestimate their competence, while high-achieving students tend to underestimate it. This may have affected the accuracy of individual self-reports. Third, the possibility of a response shift (Levinson et al., 1990) must be considered. As students' understanding of AI literacy increased, so too may their awareness of the criteria used to assess it and potentially leading to higher post-survey ratings. Finally, while the survey and interviews together provide a rich dataset, triangulation with objective performance measures or longitudinal tracking would strengthen future research designs. Nevertheless, the strong internal consistency of the findings across both methods suggests that the reported learning outcomes are robust within the given educational setting.

Conclusion

Awareness of the need for digital literacy in social work education is high, but many programs still lag in integrating these skills: Current 'research highlights a gap between the competence provided through social work education and the expectations in the practice field' (Fjeldheim et al., 2025, p. 604). The same applies to AI.

This article offers contributions toward addressing this gap. First, we are, to the best of our knowledge, the only existing research documenting the effects and potential of an interdisciplinary AI course for improving social work student's AI literacy. Secondly, we make recommendations toward a model for creating similar courses at other universities.

The goal of our course was to give students a basic technical understanding of AI and also to look at AI from a social work perspective. The students described the summer school as a transformative space where AI was demystified and made approachable. For them, the program fostered not only technical skills but also a broader sense of digital empowerment. Participants moved from apprehension to confidence, gaining the ability to engage meaningfully with AI technologies through hands-on experience, particularly in creating their own Custom GPTs.

Notes

1. For a review of AI literacy scales, see Lintner (2024).
2. See also Laupichler (2024).
3. We performed our analyses by using IBM SPSS Statistics (version 29).
4. Differences in totals are due to rounding.
5. For additional information on the social work and information technology degree see: Kilpeläinen and Päykkönen (2014). Connecting eCompetence skills to social work: the SIMO lll case as an eEducation project. In *eCompetence for social work* (pp. 109–120). Lapin yliopisto.
6. Since the spring semester of 2026, the FHNW School of Social Work has offered a compulsory module worth 3 ECTS on social work and digitalisation.

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Disclosure statement

This study was conducted in Switzerland at a Swiss school of social work. The regulatory system in Switzerland is such that studies like the one described in this article do not fall under the purview of an ethics committee for review. Nevertheless, we have ensured that all relevant ethical standards have been strictly adhered to, in order to protect participants.

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Appendix

Appendix A

The summer school programme included the following aspects:

Preparation: Ahead of the course, students received selected readings on the intersection of AI and social work (Boetto 2025; Garkisch & Goldkind, 2025), as well as a beginner-friendly introduction to the technical foundations of generative AI (Gupta 2024).

Day 1: The aim of the first day was to introduce artificial intelligence. The first part was ‘AI Unplugged’ (www.aiunplugged.org), which takes a playful approach to classification using decision trees. This was followed by a lecture on the similarities and differences between artificial and human intelligence.

Day 2: The day began with an introductory lecture on AI in social work. Participants were then able to choose two out of six workshops on exemplary uses of AI in social work.

Day 3: This day was dedicated to exploring the conditions and consequences of the social nature of technologies such as AI, as well as the ethical issues that arise. We discussed the development and possible biases of AI systems. Students also began developing their own CustomGPTs and received an input on LLMs and CustomGPTs.

Day 4: Building on the previous day, students continued to work on their CustomGPTs, under guidance for their own use cases (Fricker et al., 2025). Also, a roundtable discussion addressed the issue of responsible AI use in social work.

Day 5: The final day featured student group presentations of their CustomGPTs. The Summer School concluded with a lecture on how social work should address digital vulnerability.

A more detailed program can be found online: www.summerschool.hsa.fhnw.ch/

Appendix B

List of SNAIL items sorted by the three-factor TUCAPA-model of AI literacy (Laupichler, Aster, Haverkamp et al., 2023a)

Technical Understanding I can. . .	Critical Appraisal I can. . .	Practical Application I can. . .
describe how machine learning models are trained, validated, and tested.	explain why data privacy must be considered when developing and using artificial intelligence applications.	give examples from my daily life (personal or professional) where I might be in contact with artificial intelligence.
explain how deep learning relates to machine learning.	explain why data security must be considered when developing and using artificial intelligence applications.	name examples of technical applications that are supported by artificial intelligence.
explain how rule-based systems differ from machine learning systems.	identify ethical issues surrounding artificial intelligence.	tell if the technologies I use are supported by artificial intelligence.
explain how AI applications make decisions.	describe risks that may arise when using artificial intelligence systems.	assess if a problem in my field can and should be solved with artificial intelligence methods.
explain how 'reinforcement learning' works on a basic level (in the context of machine learning).	name weaknesses of artificial intelligence.	name applications in which AI-assisted natural language processing/understanding is used.
explain the difference between general (or strong) and narrow (or weak) artificial intelligence.	describe potential legal problems that may arise when using artificial intelligence.	explain why AI has recently become increasingly important.
explain how sensors are used by computers to collect data that can be used for AI purposes.	critically reflect on the potential impact of artificial intelligence on individuals and society.	critically evaluate the implications of artificial intelligence applications in at least on subject area.
explain what the term 'artificial neural network' means.	describe why humans play an important role in the development of artificial intelligence systems.	
explain how machine learning works at a general level.	explain why data plays an important role in the development and application of artificial intelligence.	
explain the difference between 'supervised learning' and 'unsupervised learning' (in the context of machine learning).	describe what artificial intelligence is.	
describe the concept of explainable AI.		
describe how some artificial intelligence systems can act in their environment and react to their environment.		
describe the concept of big data.		
evaluate whether media representations of AI (e.g. in movies or video games) go beyond the current capabilities of AI technologies.		