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Artificial Intelligence Chatbots in Chemical Information Seeking: Educational Insights through a SWOT Analysis

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Abstract: Artificial intelligence (AI) chatbots are the latest advance in information technology. They are next-word predictors built on large language models (LLM) that offer the possibility to process and generate information. In this theoretical article, we provide educational insights of the possibilities and challenges of educational usage of AI chatbots. The insights were produced in the context of chemical information-seeking activities designed for chemistry teacher education. The analysis was conducted via a SWOT approach using technological pedagogical content knowledge framework (TPACK) to improve the accuracy. The analysis revealed several internal and external possibilities and challenges. The key insight is that AI chatbots will change the way people interact with information. For example, they enable the building of personal learning environments with ubiquitous access to information and AI tutoring. Their ability to support chemistry learning is impressive. However, processing of chemical information reveals the limitations of current AI chatbots not being able to process multimodal chemical information. There are also ethical issues to address. Despite the benefits, wider educational adoption of AI chatbots will take time. The obstacles hindering the adoption of AI chatbots can be removed, for example, through integrating LLMs to curricula, focusing on open-source solutions, and training teachers with modern information literacy skills. This research presents theory-grounded examples of how to support the development of modern information literacy skills in chemistry teacher education. Based on the conducted analysis, we predict that AI chatbots will be a major technological change agent towards inclusive and equitable quality lifelong learning for all.

Keywords: artificial intelligence; chatbot; information seeking; chemistry learning; teacher education; TPACK; SWOT

Introduction

Artificial intelligence (AI) chatbots are generative chat tools built on large language models (LLM), such as GPT-3.5, GPT-4, PALM, and LLaMA. In the past year, AI chatbots (e.g. Bard, Bing Chat, and ChatGPT) have received great interest from the media, public, policy makers, and researchers from various fields (Bowman 2023). Educational researchers have also found generative chat engines an interesting research topic. In particular, higher education institutions (HEI) have been at the frontier of educational use of AI chatbots long before the recent public awareness of LLM-based software. This is clearly seen from several recent review articles (Okonkwo and Ade-Ibijola 2021; Dempere et al. 2023; Lo and Hew 2023). A current trend is that major companies and research institutions around the world are investing in the development of LLMs, promoting their rapid evolution. New use cases and applications are invented constantly, and AI chat technology is soon

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becoming ubiquitous (Bowman 2023). In this regard, the educational field must adopt this new technology and develop pedagogically meaningful use cases for it (Lim et al. 2023).

Technically, LLMs are statistical next-word predictors. However, from a human perspective, LLMs seem to have highly intelligent creative abilities. Bowman (2023) reviewed multiple studies where the ability of LLMs to learn and predict seem to produce novel text and representations that are valuable for users. According to Bowman, the reason for this is that LLMs are trained in a representationally rich environment through a massive amount of data using versatile training methods, including interaction with various types of software. They are also capable of conducting searches within the databases in response to user information requests (Panda and Chakravarty 2022). This is interesting from an educational perspective. For example, LLMs can pass visual tests that measure reasoning (He et al. 2021), deduce what the author knows about the topic, produce reasonable text suggestions to support writing (Andreas 2022), and generate novel images and guide users on how to draw them (Bubeck et al. 2023). The current challenge is that even though LLMs seem to provide meaningful output in many cases, there are no reliable techniques to control the content generation. There is also a learning curve to consider with e.g. prompt crafting, as a short interaction with LLMs does not seem to produce good results (Bowman 2023). To maximize success with LLMs, users need to learn how to think step-by-step and formulate prompts using an iterative process (Kojima et al. 2022).

As mentioned, scholars working in higher-education studies have been active in AI chatbot research, providing knowledge on e.g., potential use cases, risks, and students' perceptions towards its usage. For example, Strzelecki (2023) found that the three strongest reasons for higher education students to use ChatGPT in learning were habit of usage, expectations for improving performance, and hedonic motivation. These results were based on a data sample of 543 students' self-reports, thus providing a trustworthy perspective on motivational factors of early adopters. Cooper (2023) highlights potential risks of LLMs, such as fake citations, generation of biases found from training data, need for content moderation, copyright issues, and environmental impacts such as carbon dioxide emissions and high energy consumption. From a positive perspective, Jauhiainen and Guerra (2023) argue that generative AI can revolutionize digital education and offer major possibilities to support sustainable development goals, especially sustainable education SDG4. This could be achieved, for example, by using AI to provide access to high-quality learning environments and up-to-date information for all. However, the adoption of new technology increases the complexity of the information environment. This sets new requirements for teaching information literacy that must be considered in the teacher education (Dahlqvist 2021). In summary, scholars are cautious of new technology by identifying potential risks. However, these scholars also see several educational possibilities, such as a tool to create new exercises and to support writing (Crawford, Cowling, and Allen 2023; Sullivan, Kelly, and McLaughlan 2023).

Indeed, the implementation of AI chatbots is a very current topic in educational research. New articles are published constantly. Although it seems that much research has been done, according to many authors (e.g. Dempere et al. 2023; Jauhiainen and Guerra 2023; Strzelecki 2023) there is a need to develop research-based models on how to use these tools to support learning and teaching in practice. We agree with this need and use it to justify the rationale. The purpose of this article is to offer novel theory-based insights about the usefulness of AI chatbots in supporting learning. However, the challenge with this kind of broad purpose statement is that the educational usage of AI chatbots is a highly multidisciplinary topic, offering endless perspectives to address. Therefore, to make a valuable contribution to the scientific discussion, the article needs a clear focus that positions AI chatbots in an educational context. A well-defined focus requires several contextual limitations, which we describe and justify next.

First, as AI chatbots are technological applications of LLMs, we argue that AI chatbot-related educational research needs to define AI chatbots as a technological invention. This enables defining the educational adoption of AI chatbots as an innovation (Denning 2012), which is a central concept for the diffusion of new educational technology (Rogers 2003). From the research literature, one can already find multiple examples of how to implement AI chatbots in education (see Okonkwo and

Ade-Ibijola 2021; Dempere et al. 2023). However, even though there are ready-made solutions available, the field will not immediately adopt them on a broad scale. This is due to the nature of innovations. It takes time before innovation is communicated throughout the educational community, including teachers, students, and other stakeholders (Rogers 2003). Fortunately, there are ways to expedite the diffusion. Ertmer et al. (2012) suggests that the adoption can be supported by identifying and removing barriers that hinder teachers' usage of new technology.

Obstacles can be external or internal. External challenges are called first-order barriers, such as hardware, software, training, and support. Second-order barriers are internal challenges, such as teachers' beliefs, attitudes, skills, knowledge, confidence, and experienced value for supporting teaching and learning (Ertmer and Hruskocy 1999). First-order barriers are significant and can prevent technology usage completely. However, they are often clearly identifiable and removed rapidly (Ertmer et al. 2012). For example, when ChatGPT was released for public use on 30 November 2022, it instantly removed barriers related to software access (OpenAI 2022). Training and support can also be arranged rapidly if needs are identified and there are available resources for training. Therefore, the second-order barriers are the real challenge in supporting the adoption of educational technology. Teachers will not start using new tools without skills and understanding of their possibilities and challenges (Ertmer et al. 2012). This is the reason why we focus on removing the second-order barriers by providing insights into the educational possibilities and challenges of AI chatbots usage.

There are several research-based frameworks that support modeling of knowledge domains required in describing the full innovation environment. In this research, we have selected a technological pedagogical content knowledge (TPACK) framework for the modelling tool (Koehler, Mishra, and Cain 2013). TPACK was selected because it is a widely used framework and there are several successful research cases where it has been used in modeling the knowledge domains that affect adoption of educational technology (Voogt et al. 2013).[1] First-order barriers are mainly related to technological knowledge (TK) and are easily identified in the case of AI chatbots. However, the removal of second-order barriers requires pedagogical knowledge, which adds complexity to the innovation work.

Second, to contribute directly to the educational discussion, the article needs a pedagogical context. For the pedagogical knowledge (PK) component, we have selected information seeking. In this article, we define information seeking as purposive interaction with information (Ingwersen and Järvelin 2005) (see section 2). The context was selected because good information-seeking skills are essential in academic work (Gordon et al. 2018) and present in all learning and problem-solving activities to some extent (Shultz and Li 2016). In addition, the topic is important for the educational sector because teachers need new tools on how to manage the rapidly expanding information environment. Lack of information skills can lead to inequality between people (Parissi et al. 2023). Without up-to-date information literacy skills, teachers cannot promote lifelong learning skills and support the sustainability and equality of education for all (SDG4) (Dahlqvist 2021).

There is also a gap in research that combines AI chatbots and information seeking in an educational context. Therefore, information-seeking context makes this research interesting also for the field of information sciences. There is a shortage of task-specific technology-driven information-seeking studies (Järvelin and Ingwersen 2004; Ingwersen and Järvelin 2005), and more research is needed whenever new tools and technology are developed (Zamani et al. 2023).

The third contextual limitation is derived from the content knowledge (CK) component of TPACK framework (see Figure 1). We have included the content knowledge perspective into the innovation environment by conducting the research in an authentic higher education setting of chemistry teacher education. This enables us to analyze the selected technological and pedagogical contexts through chemical information.

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[1] An in-depth overview of the TPACK framework can be found in section 3.2.

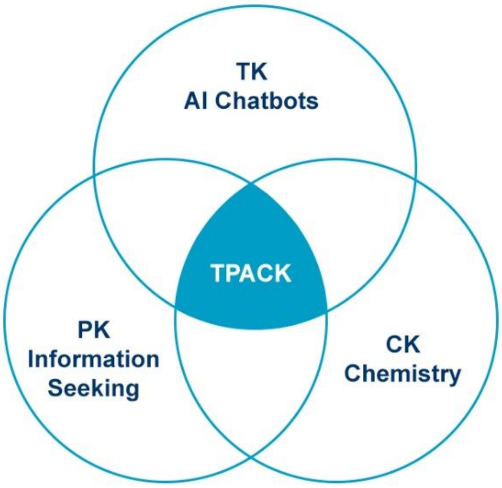

Figure 1. A TPACK illustration that describes the three knowledge domains that sets the contextual limitations of the research: 1) AI chatbots represent technological knowledge (TK), 2) information seeking is addressed as pedagogical knowledge (PK), and 3) chemistry is content knowledge (CK).

With these three contextual limitations and the selected higher educational setting, we can formulate a clear focus. The aim of this theoretical research is to analyze the possibilities and challenges emerging when AI chatbots (TK) are applied in educational information seeking (PK) of chemical information (CK) in pre-service chemistry teacher education (HEI). The analysis was conducted by first preparing a narrative literature review (Green, Johnson, and Adams 2006) on information seeking (see section 2). The insights of the literature review were used in designing educational chemical information-seeking activities that were analyzed via a SWOT approach (Benzaghta et al. 2021). The educational use cases of AI-assisted information seeking were specifically designed for future chemistry teacher education courses at the University of Helsinki. To ensure pedagogical diversity, we present one example from each core knowledge component of TPACK (see section 3). We analyzed the possibilities and challenges via SWOT, which was guided with the following research question: what kind of strengths, weaknesses, opportunities, and threats does AI chatbot-assisted information seeking offer for chemistry teacher education? In section 4, we report the analysis results and reflect them on the presented background literature. Lastly, in section 5 we present a summary and research-based conclusions organized using the SWOT model.

Through this research design (see Figure 2), we can produce novel insights and address the stated broader purpose from a unique interdisciplinary perspective that is especially relevant for chemistry teacher education. This research contributes to the identified research gaps by providing research-based knowledge that is useful for all who design educational AI chatbot applications, use cases, and pedagogical models.

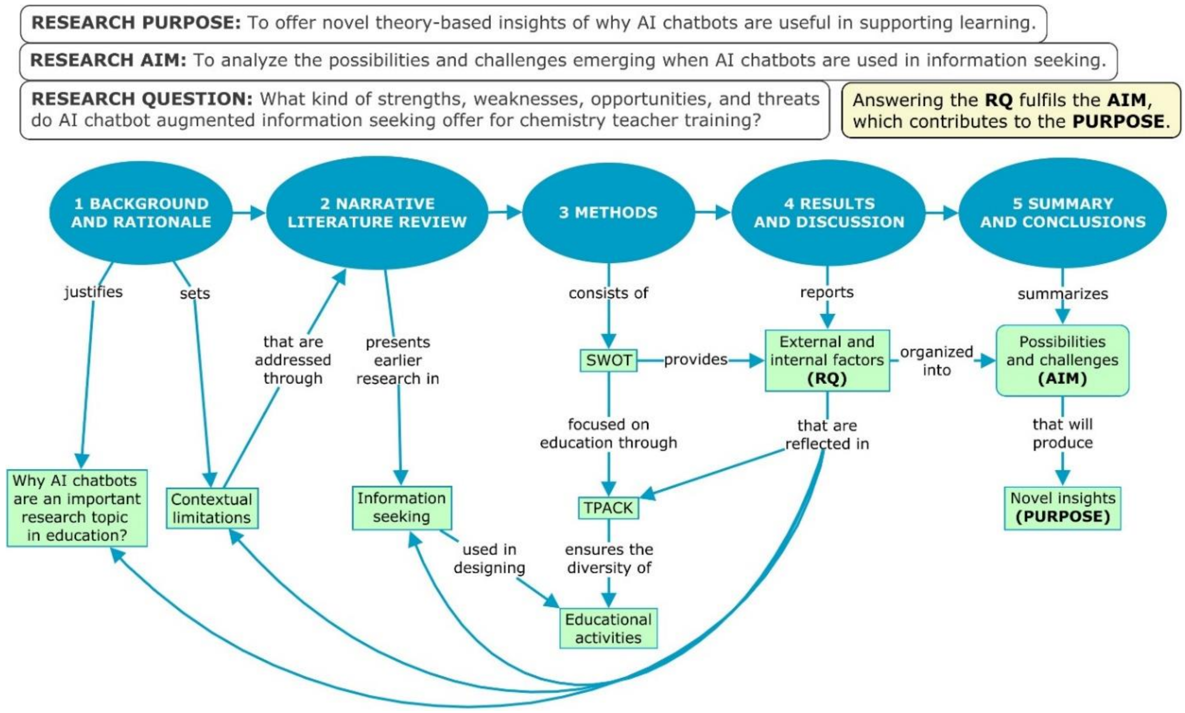

Figure 2. Overview of the research design that illustrates the relations between research purpose, aim and question.

Theorical Background of Information Seeking

To understand AI-assisted information seeking as a theoretical concept in pedagogical context, we start by defining broader concepts such as information, information behavior and information seeking. Then we proceed to contextual level and review AI chatbot-assisted information-seeking literature (see section 2.1). Last, we shift the focus to chemistry and explore earlier research related to chemical information seeking (see section 2.2.). For defining the central concepts, we have used core literature in the field of information science with hundreds or even thousands of citations. With this approach, we aim to use widely accepted definitions that as many readers as possible recognize and agree upon.

In information sciences there are two common models of how to describe and define the concept of information. The models partly overlap because both describe information as dynamic by nature. The first model is derived from Popper's epistemology. According to this, information can be internal or external and has many locations, such as a person's mind, electronic storage, or physical documents. However, the key idea is that the purpose of information is to communicate knowledge between various stakeholders and systems (i.e., Popper's three worlds) (Bawden and Robinson 2012). The second model illustrates the structures of information space and emphasizes its dynamic nature through a refinement process. Refinement is usually described as a linear progression where data is first refined to information, and knowledge understood as refined information. The last stage is to develop knowledge to wisdom, expertise, or actions (Bawden and Robinson 2012; Bawden 2001).

Refinement requires interaction between people, information, and information channels, which is called information behavior. It can be active or passive, but it is always context dependent, reflecting parameters set by real-life situations (Wilson 2000). For example, information context can be related to work tasks or holiday planning. Different contexts require different accuracy and available information channels are slightly different. In this regard, context affects the tasks that ignite and shape the need for information. Information needs are fulfilled through information seeking. Purposive information behavior consists of cognitive processes such as remembering, creating, or acquiring knowledge that aims to fulfill the information need (Järvelin and Ingwersen 2004; Ingwersen and Järvelin 2005).

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In Figure 3, we combine the widely used information behavior model (Wilson 1999) and the information-seeking model (Järvelin and Ingwersen 2004; Ingwersen and Järvelin 2005) to illustrate the relation between context, information behavior, and information-seeking strategies. Through this renewed hybrid model, we highlight the importance of context that affects tasks that formulate the actual information need. Tasks are concrete units of information behavior that allow us to design educational information-seeking activities that apply AI chatbots (see Section 3.3).

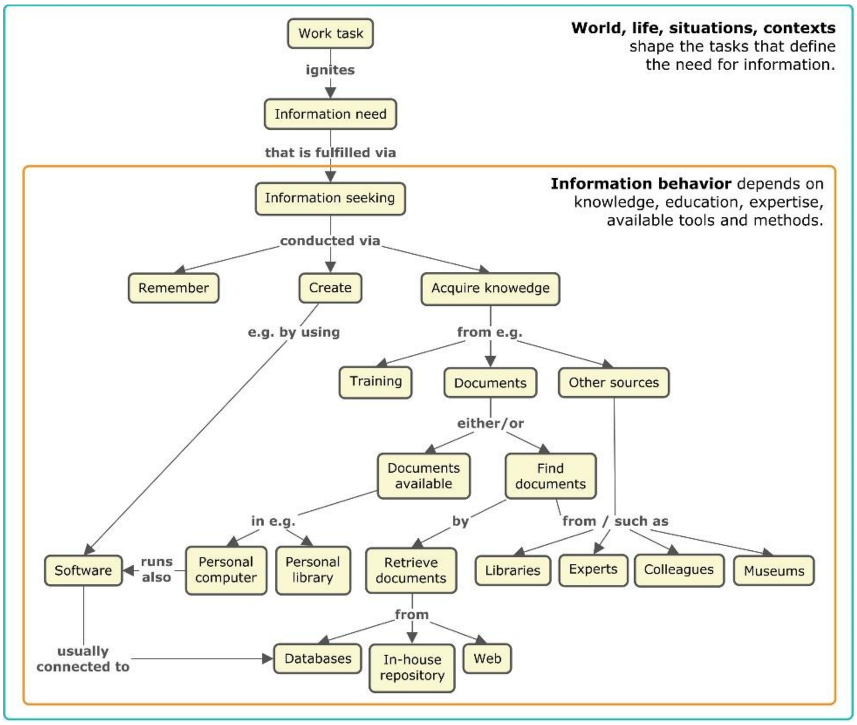

Figure 3. A Renewed Information-Seeking model built by merging Augmented Information-Seeking model (Järvelin and Ingwersen 2004; Ingwersen and Järvelin 2005) and the Nested Model of Information Behavior (Wilson 1999).

AI Chatbots and Information Seeking

From an information-seeking perspective, chatbots offer a conversational interface for information search (Liao et al. 2020). Their usage has been studied for several years before the recent public awareness of AI chatbots. Brandtzaeg and Følstad (2017) conducted one of the first empirical studies that mapped out the motivational factors behind chatbot use. According to their quantitative study (N=146), the most frequent reason for use was to increase productivity. The second most observed reason was entertainment; the third was to use chatbots for social purposes. Many respondents felt that chatbots have social value by providing the possibility to have human-like interaction. These early results differ slightly from Strzelecki's study (2023), which highlighted habit of usage in addition to production and enjoyment. However, it is noteworthy that Brandtzaeg and Følstad already predicted in 2017 that conversational chatbots will create a new paradigm in how people interact with data, information, and services.

Avula et al. (2018) studied chatbot usage in collaborative information seeking. Technically, chatbot tools can be integrated directly inside the workflow software or they can be used as separate software. Avula and co-authors found that task difficulty and users' prior knowledge influenced their motivation to use chatbots. A combination of difficult tasks and little prior knowledge increased usage. Note that the chatbots used over 5 years ago were not based on LLMs. The GPT-1 model was published in 2018 (Radford et al. 2018). Regardless of the technology, the main reason to use chatbots in information seeking is to find relevant information efficiently (Lommatzsch and Katins 2019).

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According to our previous research, fulfilling an information need is an often-mentioned rationale for chemical information software development (Pernaa et al. 2023). The same justification is also used in developing AI chatbot solutions. For example, Androutsopoulou et al. (2019) developed an AI chatbot that assists people in using public services. The objective was to support communication between citizens and government, which would increase well-being and decrease administrative costs. Another mentioned design objective for AI chatbots is to develop more personalized services (Panda and Chakravarty 2022). Personalization has both economic and social value. Matching consumer and chatbot personalities increases consumer engagement, which positively affects purchasing behavior (Shumanov and Johnson 2021).

Conversational tools also offer possibilities for educational information seeking. According to Adarkwah et al. (2023), AI chatbots provide instant feedback, such as a face-to-face human tutor. It can be used in generating summaries and new insights that can enhance the interaction with information and support learning. AI chatbots are also excellent in translating text, thus fostering multilingual collaboration. However, all LLMs and software have limitations, such as biases and fake citations (Cooper 2023). Adarkwah et al. (2023) emphasize that learners must be aware of the possibilities of the new technology and understand the challenges. They suggest that it is essential to seek a balance between the new tools and traditional information resources, such as libraries, databases, teachers, and other professionals.

Information Seeking in Chemistry

There are few previous studies on chemistry-specific information seeking. Chemistry, similar to many other research fields, is very broad. New findings are published daily, and keeping up with the latest information is overwhelming for many chemists (Flaxbart 2001; Gordon et al. 2018). The amount of chemical information is massive and can be in various formats, such as text, diagrams, numbers, chemical symbols, line notations, molecule files, photographs, videos, 2D representations, and 3D models. It is often delivered in multimodal format (Wegner et al. 2012), which can be communicated at three different levels of chemical information (see Figure 4). The macro level communicates concepts that can be seen. The symbolic level expresses chemistry through chemical symbols. The submicroscopic level illustrates the unseen atom, and the particle level describes dynamic chemical interactions (Johnstone 1982). The triplet model of chemical information is one of the key models in chemical education research and is used to illustrate the complexity of chemical information (Gilbert and Treagust 2009). The complexity of information may cause cognitive overload, which is often used to explain why chemistry is a difficult subject to learn (Johnstone 1991; Gabel 1999; Reid 2019).

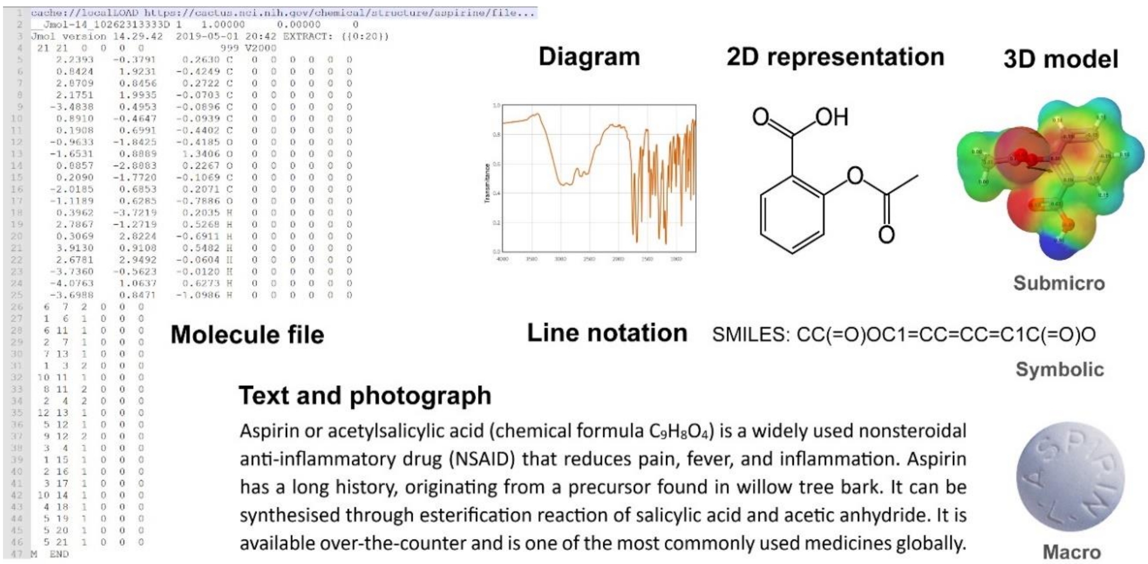

Figure 4. Example of the diversity of representations in chemical information. All information formats describe the characteristics of acetylsalicylic acid from different perspectives.

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Due to the amount of chemical information and its complexity, many chemists feel that "*there is too much information and not enough time*" (Gordon et al. 2018, 130). According to Gordon et al. (2018), from a data sample of 245 chemists, only 13.9% of chemists felt that they were successful in following the latest advances in the field. About 50% of the respondents felt that they were somewhat successful, and the rest felt the need for improvement. On the other hand, in Flaxbart's (2001) qualitative data sample (N=6), almost all chemists considered their information-seeking skills as good or expert level. This research result might be because all respondents were at least PhD-level academics, and it was conducted years before the massive growth of digital chemical information (Ferk Savec 2017). According to Parissi et al. (2023), good content knowledge is the foundation of efficient information seeking. Overall, a major challenge is that one needs several information strategies to be successful, which should be addressed in chemistry university studies (Flaxbart 2001; Gordon et al. 2018).

According to Shultz and Li (2016), there is a great need to improve the information-seeking skills of chemistry undergraduate students. They found that students were unable to recognize the information needs or to evaluate the quality of information resources. This led to the novice-level work process of trying to find direct answers to problems, often using non-scholarly literature. Shultz and Li (2016) suggested that the information-seeking skills of chemistry students may be scaffolded via information literature training and carefully designed information-seeking exercises. The research results of Parissi and co-workers (2023) support this proposition. They found that educational information-seeking tasks and improved content knowledge increases the variety of information-seeking actions.

AI chatbot-assisted information seeking has also arrived in the field of chemistry. There are preprints that offer preliminary benchmarks of the possibilities and limitations of AI chatbots for chemistry research (Guo et al. 2023; Hatakeyama-Sato et al. 2023) and learning (P dos Santos 2023). Preliminary results indicate that AI chatbots can scaffold learning by enhancing chemical information seeking significantly. They offer an interface to dynamic personalized learning discussions that support the development of conceptual knowledge and fosters critical thinking (P dos Santos 2023), such as analyzing and evaluating, which are higher-order cognitive skills (HOCS) (Krathwohl 2002). For example, the user can prompt answers for basic-level questions, acquire new chemical insights through learning discussions, or obtain support to plan chemical experiments (Hatakeyama-Sato et al. 2023). This enables building of personal learning environments and provides equal possibilities for all to expand their zone of proximal development (ZPD) (Vygotski 1978; Fernández et al. 2001; Mott and Wiley 2009; Peña-López 2013), which supports sustainable education goals (SDG4) (United Nations n.d.). To use AI chatbot technology efficiently, it is important to learn prompt crafting (P dos Santos 2023).

Methods

SWOT analysis

SWOT is a descriptive method that enables analysis of possibilities and challenges by categorizing features to internal strengths and weaknesses and external opportunities and threats (Gürel and Tat 2017; Benzaghta et al. 2021). Therefore, SWOT offers more analytical accuracy than just focusing on possibilities and challenges, which is why we have chosen this as the analysis approach. Although SWOT was originally developed in the 1960s to support strategic business planning (Puyt, Lie, and Wilderom 2023), due to its practical nature, there are several research examples where SWOT has been applied in analyzing educational technology contexts, such as 360° virtual reality (Kittel et al. 2020; Roche et al. 2021), educational cheminformatics (Pernaa 2022), and sports technology (Verdel et al. 2023).

In addition, because our research context is highly interdisciplinary, combining learning, information seeking, and educational technology, we decided to add an extra layer to SWOT to improve the accuracy even further. To ensure that the analysis is focused strictly on educational possibilities and challenges, we used the TPACK framework to guide the analysis inside SWOT sections (Mishra and Koehler 2006).

TPACK Framework

TPACK is a widely adopted model that facilitates understanding of different knowledge types needed for successful use of educational technology. The TPACK framework consists of several overlapping knowledge domains, often visualized through a Venn diagram (see Figure 5) (Koehler, Mishra, and Cain 2013). The three already introduced core components are PK (how to learn or write), CK (concepts, theories, and research techniques), and TK (knowledge of devices, software, communication tools). The interaction of the core components forms three hybrid knowledge categories. Pedagogical content knowledge (PCK) is, for example, knowledge of challenges in learning some specific concept. In this research, PCK refers to the interaction of chemical information and information seeking. Technological content knowledge (TCK) enables using technology to support learning of some specific concepts. In this research, the usage of AI chatbots for interacting with chemical information is considered TCK. Technological pedagogical knowledge (TPK) is understanding the possibilities that technology offers for learning. In this research, prompting technological advice is considered TPK (Koehler and Mishra 2005; Mishra and Koehler 2006; Koehler, Mishra, and Cain 2013). Note that TPK is not subject specific and does not overlap directly with CK (see Figure 5).

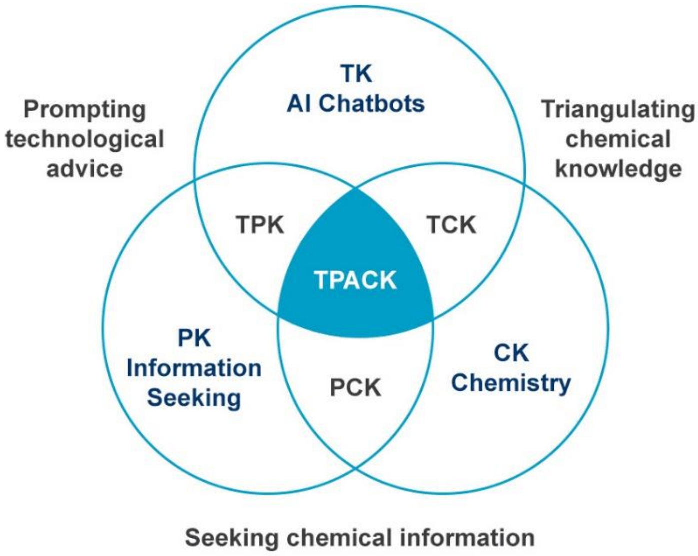

Figure 5. A model of the TPACK framework with TPK, TCK, and PCK examples from this research.

The TPACK model has been criticized for being rather unclear or unpractical (Willermark 2018). One problem is the diversity and inaccuracy of definitions for different knowledge components (Graham 2011). For example, Cox (2008) analyzed TPACK research literature and found 13 definitions for TCK, 10 definitions for TPK, and 89 definitions for TPACK. Such variance makes it difficult for researchers to understand and use the framework systematically to support diffusion of innovations and to measure different TPACK domains in consensus. For example, TK includes all modern (e.g. smartphones, internet, and AI chatbots) and traditional technologies (e.g. pencils and chalkboards) under the same knowledge domain (Graham 2011). Because of this broad categorization, some researchers have developed more accurate definitions. For example, Angeli and Valanides (2009) have conceptualized a knowledge domain called ICT-TPCK to represent the information and communication technological aspects of TPACK. Some criticism has also been directed towards the actual TPACK visualization (see Figure 5). Graham (2011) argues that according to the TPACK model visualization, PK is not needed in TCK (no overlap between PK and TCK).

Nevertheless, there are still many TCK definitions that include the aspect of learning. Graham emphasizes that there is a lot of work to be done in defining TPACK and its knowledge components, because *"precise definitions are essential to a coherent theory"* (Graham 2011, 1955).

We agree with the inaccuracy claims of the TPACK model. Every model has its strengths and limitations. The authors cited have provided constructive criticism that has supported the development of the TPACK concept. Despite the criticism, TPACK has been used successfully in hundreds of research cases in modeling the knowledge components needed to use educational technology. Therefore, we are confident in using TPACK to increase the analysis accuracy of our SWOT analysis.

Designed AI Chatbot-Assisted Information-Seeking Activities

Next, we present the three designed AI chatbot-assisted information-seeking activities that will be analyzed using SWOT. Activities 1 and 2 are included in the course "ICT in Chemistry Education", which is a 4 ECTS mandatory course for bachelor studies of chemistry education at the University of Helsinki. Activity 3 was designed for an advanced master's level chemistry education course called "Inquiry and integration in chemistry education".

Activity 1: Write a Summary (PK to TPACK)

In the first activity, chemistry student teachers were assigned to read an article about microcomputer-based laboratories (Aksela 2011) and write a 250-word summary in Finnish. The designed information need was to become orientated with the topic before laboratory work. The information behavior needed to complete this assignment leaned strongly towards creating knowledge (see Figure 2) (Ingwersen and Järvelin 2005).

We supported the work process via the following instructions:

1. Generate a summary from the article via AI-PDF software (for example, pdf2gpt software [https://pdf2gpt.com]).
2. Ask an AI chatbot tool (e.g., ChatGPT, Bard, or Bing Chat) to refine it to 250-word length.
3. Translate the text to Finnish via the same tool.
4. Examine the text, correct language and readability, and add the required infographic or table mentioned in the evaluation criteria.
5. Describe the entire working process (prompts included) below the summary sufficiently precisely such that it can be repeated if desired.
6. Reflect on the possibilities and challenges of the work process in 250 words.

We categorized this activity under PK, as academic writing is not always CK dependent. Software tools represent the TK domain, making the driving factor of the assignment TPK. However, the context of the activity is microcomputer-based laboratory (CK), which is why it ultimately activates the entire TPACK framework (Mishra and Koehler 2006; Koehler, Mishra, and Cain 2013).

Activity 2: Create a Concept Map (CK to TCK)

The second activity was a concept-mapping exercise. In this exercise, chemistry student teachers chose a chemical concept found in the Finnish curriculum, such as energy or a chemical reaction. The students then made a Novakian concept map including about 20 concepts, 3-4 hierarchy levels, links, and images (see Novak and Cañas 2006).

This exercise activates all three major information-seeking strategies (Ingwersen and Järvelin 2005). Our design conjecture was that students will remember some concepts but not all 20. Therefore, they must acquire conceptual knowledge and create relations between them. In this regard, the information need was to remember basic-level chemistry knowledge and model a larger conceptual system. To acquire chemical information and to create relations between concepts, they were encouraged to use AI chatbots and textbooks. The role of AI chatbots was to strengthen the internal work process by offering a tool for triangulating ideas, supporting the design of conceptual limitations, and verifying memory-based definitions.

This exercise was categorized under CK because it focused on chemistry. However, because the concepts were prepared using software, and the overall aim was to learn how to visualize chemical concept structures, the exercise also has TCK emphasis (Koehler, Mishra, and Cain 2013).

Activity 3: Build a Chemistry Measurement Instrument (TK to TPACK)

In the third exercise, students designed and built a chemistry measurement instrument using a single-board computer platform. In addition, they created a project-based learning module that used the device. This exercise was very challenging for chemistry student teachers because it required programming skills and electronics construction experience in addition to chemistry and pedagogical knowledge. These skills are not included in their study program by default, but are developed through optional studies or hobbies (Ambrož et al. 2023).

The basis of this exercise is TK, due to the electronics and programming demands. However, this exercise also required CK for the chemistry context and PK for the pedagogical planning. Therefore, we argue that it can be used in developing whole TPACK (Koehler and Mishra 2005). This exercise was the most challenging from the information-seeking perspective. Building a chemistry device with a pedagogical purpose requires remembering, creating, and acquiring knowledge through diverse resources. The task likely activated all information behavior components presented in Figure 3 (Järvelin and Ingwersen 2004; Ingwersen and Järvelin 2005).

Results and Discussion

Supporting Writing Assignments

As discussed in the introduction, several scholars have studied the possibilities and challenges of AI chatbots for writing. Some are concerned on how chatbots affect the development of writing skills; others focus on its benefits (Sullivan, Kelly, and McLaughlan 2023). Although students already use chatbots widely, it is hard to detect which is an internal weakness.

To adopt AI chatbots meaningfully in higher education, the University of Helsinki has taken a constructive approach and is not focused on controlling but rather on teaching how to use new technology. The Faculty of Science offers support to faculty personnel on how to guide students in using AI chatbots in courses (see appendix A). Some use cases may be allowed, others forbidden, but the key is to make course-dependent decisions based on the learning objectives. This is an external opportunity to teach students about the ethical considerations in academic writing (Crawford, Cowling, and Allen 2023). Faculty-level actions are essential in coordinated systematic innovation work. This kind of instructive communication towards faculty personnel especially supports the removal of second-order internal barriers, such as beliefs and attitudes (Ertmer et al. 2012).

Our design conjecture was that the use of AI chatbots offers many internal strengths, such as increasing productivity by expediting preparation of the summary (Sullivan, Kelly, and McLaughlan 2023; Strzelecki 2023; Brandtzaeg and Følstad 2017). From a course-planning perspective, this is an opportunity that allows allocating fewer hours to CK orientating and more time for laboratory work. From a writing perspective, AI chatbots change the focus of skills that will be developed. Previously, the emphasis was on writing text; with chatbots the emphasis is now on analyzing and evaluating text and editing it to ensure fluency. Therefore, chatbot-assisted writing fosters critical thinking and can be used in developing academic writing skills (P dos Santos 2023). However, one must understand that chatbots support different kinds of writing skills. Some might see this as an external threat for academic skills in general. However, we argue that this is neither an internal strength nor a weakness depending on the perspective.

The translation abilities of AI chatbots are not limited to English (Adarkwah et al. 2023). This offers an external opportunity to expand the language pool of the selected course literature. For example, there is considerable chemistry education research literature published in German, French, and Spanish that are not commonly used in Finnish academia. In addition, language-processing capabilities enable foreign students with modest English skills to interact with the course literature more seamlessly than before. When chatbots develop further, they could even contribute to writing

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exercises in a multilingual group assignment. This offers an external opportunity to support the inclusion and equity of education (SDG4) (United Nations n.d.). However, the selected software should be open source and sustainable such that every learner has an equal opportunity to use them. For example, in our activity 1 we recommended pdf2gtp software, which has subsequently announced that the free version will have restrictions in the future and a pro version with a small fee will be published. This is an example of an external threat derived from TK domain.

Triangulating Basic Level Conceptual Knowledge

The second activity introduced students to concept mapping. A concept map is a meta-level knowledge tool especially useful for making internal conceptual structures visible, which facilitates communication between stakeholders and enables refining information from data to expertise (Wilson 1999; Novak and Cañas 2006; Bawden and Robinson 2012). While designing the activity, we saw the possibilities that AI chatbots offer for learning discussions. Users can have meaningful chemistry-related conversations with chatbots, but as highlighted in the literature, good prompt-crafting skills are essential for successful workflows (P dos Santos 2023). In addition, we realized how important it is to critically analyze the answers that AI chatbots return. For example, some of the Finnish names for concepts and their definitions were nonsensical. This sets requirements for the user's CK. The user must have at least a basic-level understanding of the topic to evaluate the quality of the output. This is an internal weakness derived from AI chatbot technology. On the other hand, this offers an opportunity to activate HOCS, such as analyze and evaluate (Krathwohl 2002).

In this research, we mainly used the free version of ChatGPT based on GPT 3.5 in developing the exercises (OpenAI 2022). From a chemical information perspective, the free version of ChatGPT can help understanding at all three levels (Johnstone 1982; Gilbert and Treagust 2009), although outputs are delivered in text format. This is an internal weakness. Users can make a submicroscopic level prompt and the chatbot will describe the dynamic nature of chemistry through a textual description (see Figure 4). However, these outputs can be used in clarifying some specific illustrations and could decrease the potential cognitive overload (Gabel 1999; Reid 2019). In this sense, a triangulation of knowledge through a combination of traditional information resources (such as textbooks) and modern tools (such as chatbots) can be a good workflow before more integrated solutions are developed (Adarkwah et al. 2023).

Scaffolding Usage of Unfamiliar Technical Knowledge

During the development of activity 3, we observed that AI chatbots can produce functional well-commented source code and circuit planning. This was the case at least with the educational Arduino platform. As our earlier research indicated, we have a major challenge in introducing coding and SBC-based chemical instrument development for chemistry student teachers because the diverse knowledge requirements cannot be addressed in a single 5 ECTS university course (Ambrož et al. 2023). Through AI chatbots, we can significantly decrease the workload related to programming and electronic device planning. For the output analysis need, the software development platforms offer internal quality tools by default. Users can test and debug whether the written code works as intended. This is an external opportunity to teach software development and an internal strength raised from the ability of AI chatbots to generate working source code. However, prompt crafting is again the central skill that should be taught to students (Kojima et al. 2022).

From the information-seeking perspective, this is the most challenging activity. It includes many unfamiliar knowledge domains that require considerable independent problem solving. Of course, students can ask for help from teachers. Unfortunately in reality, teachers do not have enough resources to assist every student in every single support request (Ambrož et al. 2023). To develop good problem-solving abilities and persistence, students must learn how to cope by themselves using their personal networks as support. This is also important from the work-life requirements perspective. As a solution, we see that AI chatbots offer an external opportunity to build a personal learning environment and expand their ZPD (Fernández et al. 2001; Peña-López 2013). For example, if the learner does not understand some parts of the code, they could make clarifying prompts.

However, to develop good information literacy skills, we claim that it is important to learn how to use versatile information resources, such as libraries, document retrieval, and contact with experts (Shultz and Li 2016). This would ensure the development of diverse information behavior (Ingwersen and Järvelin 2005; Dahlqvist 2021).

Summary and Conclusions

The conducted TPACK-guided SWOT analysis revealed several possibilities and challenges both from the internal and external perspectives (see Table 1). According to our evaluation, the TPACK as a modeling framework worked as planned and offered more analysis accuracy for categorizing the insights inside the SWOT model (Koehler, Mishra, and Cain 2013). This enables focusing the innovation work to a specific knowledge domain.

First, we agree with Brandtzaeg's and Følstad's (2017) prediction in that AI chatbots will create a new paradigm for how people interact with information. AI chatbots represent cutting-edge information technology that will soon be applied throughout society in all kinds of tasks to increase productivity (Bowman 2023; Strzelecki 2023). AI chatbots offer opportunities for information seeking by providing a conversational interface and access to a limitless information resource for all (Liao et al. 2020; Jauhiainen and Guerra 2023). Their translation capabilities and ability to have learning discussions enable building of high-quality personal learning environments and expanded ZPDs that will offer personalized learning experiences for everyone regardless of language or cultural background (Fernández et al. 2001; Peña-López 2013; P dos Santos 2023; Adarkwah et al. 2023). For maximizing ZPD, we predict that in the future there will be more integrated software solutions built to support collaborative information seeking (Avula et al. 2018). The possibilities to support sustainable education are endless. We claim that AI chatbots will be a major change agent towards inclusive and equitable quality lifelong learning for all (SDG4) (United Nations n.d.).

However, it is important to understand that AI chatbots are an invention and their educational adoption will take time (Denning 2012; Rogers 2003). This can be supported through innovation work aiming to remove first- and second-order barriers (Denning 2012; Ertmer et al. 2012). For example, HEIs must offers licenses, support, training, and easily adopted use cases and frameworks for teachers (see Appendix A). For removal of first-order barriers, to minimize the external threats related to sustainability of selected software, we recommend that HEIs should favor LLMs and software based on open-source code. In addition, as Ertmer et al. (2012) emphasize, second-order barriers are the true challenge. We agree with this claim, and we highlight the role of teacher education as a solution. Schools may have recommendations for AI usage in teaching, but in many countries, teachers have great autonomy in making pedagogical decisions, such as whether they include AI chatbots to teaching or not. During their higher education studies, chemistry student teachers build professional identity, including perceptions and beliefs towards the new technology. Negative attitudes can be persistent, and it is more difficult to change them later in working life. This research shows an example of how to support the removal of second-order barriers though educationally meaningful learning activities. The development process of such activities can be improved further by implementing a co-design approach, which enables inclusion of expertise from several different stakeholders in the process (Aksela 2019). This is crucial in a multidisciplinary innovation environment, such as the case of using AI chatbots in seeking chemical information.

Chemistry education and teacher education will benefit from AI chatbots similarly to any other domain. Learners can refine information to knowledge via learning discussions, check facts, and prompt definitions for concepts (Bawden and Robinson 2012; Hatakeyama-Sato et al. 2023). However, one must be aware of the limitations of LLMs and analyze or triangulate the generated information before using it. This is an important information literacy skill related to usage of AI chatbots that should be included in chemistry education programs. In addition, from the chemical information perspective, AI chatbots are currently limited in processing multimodal representations in three different levels (Wegner et al. 2012; Reid 2019). In the future, AI tools will surely expand their ability to work in a multimodal information environment with visual inputs and outputs. In addition,

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they will likely be able to guide users to original information sources used in the training data. These kinds of features would definitely help the information seeking of chemists (Gordon et al. 2018).

Table 1. Summary of the synthesized possibilities and challenges categorized via a SWOT model and reflected to TPACK framework (Koehler, Mishra, and Cain 2013).

	Possibilities	**Challenges**
Internal	Strengths • Teach modern AI-assisted information-seeking processes (TPACK) • Diversifies information behavior (TPAC) • Increases productivity (TCK/TPK) • Can be used in activating HOCS skills (PK)	Weaknesses • If not allowed, usage is hard to detect (TPK) • The need for critical thinking and content knowledge to detect biases (CK) • The output needs to be verified via triangulation (CK) • Not able to produce multimodal chemical visualizations, produces textual outputs (TCK)
External	Opportunities • Can be used to include embedded knowledge, such as ethics of academic writing (TPK) • New opportunities for course planning, such as work time allocation and multilingual literature (TPK) • Supports inclusion and equity (SDG4) e.g., via translation features (TPACK) • Can be used to expand ZPD (PK)	Threats • Adoption requires innovation work (TPACK) • Selected software solutions might not be sustainable (TK) • Successful workflow requires prompt crafting knowledge that might not be included in earlier information literature studies (TPACK) • Changes the skillsets that different exercises develop (TPACK)

Based on our theoretical insights, we believe that AI chatbots will change the way people interact with information-processing tasks and what is considered expertise. In the future, everyone will have access to endless information through their high-quality personal learning environment with an embedded AI tutor. Teachers must be trained on new information literacy requirements. For future research directions, we suggest that it would be important conceptualize what is considered knowledge and expertise in the modern information age. Educational practices and evaluation culture throughout the educational field should then be renewed to support development of a new understanding of learning.

Finally, to achieve a wider change, use of AI chatbots must be included in information literacy skills and integrated in every educational level, from primary to higher education (including lifelong learning). This integration must be done at the curriculum level, which will slowly resonate as a

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change in school practices. This is especially important for teacher education. Without modern information literacy skills, teachers will not be able to support sustainable education and lifelong learning. Therefore, we challenge teacher-education programs around the world to include AI-assisted chatbot information seeking into their curricula and to show leadership at the frontier of education by changing the future of education, one teacher at a time.

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Appendix A: Use of Large Language Models in this Course

Large language models (LLM) are recently developed, versatile tools. Although LLMs have useful use cases, they can also conflict with learning objectives. Permitted uses are always course-dependent. Permitted and prohibited uses are listed below. Some uses may not be listed because they are not relevant to this course. Common language models can produce false, misleading, or irrelevant information. Because of this, it is the student's responsibility to ensure the correctness and relevance of the information. It is also worth remembering that specialized tools usually produce better results than language models. Presenting the generated text as your own can be interpreted as plagiarism. More information can be found at https://studies.helsinki.fi/instructions/article/what-cheating-and-plagiarism.

The course can specify that if a language model is used, its use must be reported. In such a case, more detailed instructions are presented in the listing below.

The use of language models in this course is:

(REMOVE UNNECESSARY SECTIONS FROM THE FOLLOWING)

- Fully allowed/forbidden.
- Allowed/forbidden to generate text for e.g., report, thesis, or certificates.
- Allowed/forbidden to finish or rewrite the text.
- Allowed/forbidden to check grammar mistakes.
- Allowed/forbidden as a typesetting aid (e.g. generating Latex code when making tables or graphs)
- Allowed/forbidden in searching for information or explaining or summarizing topics.
- Allowed/forbidden in code generation.

This instruction was written by Kjell Lemström, Senior University Lecturer, Director of the bachelor's program in computer science, Department of Computer Science, Faculty of Science, University of Helsinki, Finland.

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