Let's Chat about This - A Template for Well-Aligned AI Integration in Schools

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***Abstract*—Artificial Intelligence (AI) in general and chatbots in particular are gaining more and more attention in education. However, there are several barriers hindering teachers from using chatbots in the classroom. Based on existing empirical research on the use of chatbots in the classroom, we identify these barriers and derive systemic requirements. We suggest Retrieval-Augmented Generation (RAG) systems as an adequate solution. Unfortunately, commercial RAG systems fail to harness the full potential of this technology. Based on a requirement and market analysis, we present a locally hosted open-source, low-code RAG system template, which fulfills the requirements for use in school. We report lessons learned from our work with a Professional Learning Community (PLC) with teachers, where we continuously test and discuss our RAG system template.**

***Index Terms*—Artificial Intelligence, Retrieval-Augmented Generation, Chatbot, School, K–12 education**

I. Introduction

The development of Artificial Intelligence (AI) has gained significant momentum in recent years. Advances in computing power, data availability, and algorithms have enhanced AI tools, expanding their applications in scholarly settings. Notably, chatbots powered by large language models (LLMs) have gained widespread usage. These chatbots offer considerable potential for the use in school (e.g. as automated tutoring systems) [1]. However, several barriers, including legal, accessibility, personal, and integration challenges, hinder teachers from fully leveraging this potential. To make chatbots appealing to teachers, it is essential to address and reduce these barriers.

In previous work, we proposed Retrieval-Augmented Generation (RAG, [2]) chatbots as a potential solution for the use in education [3]. RAG chatbots offer several advantages over common chatbots like ChatGPT, particularly by lowering the integration barrier for teachers. With RAG, AI systems can be tailored to meet both the needs of learners and the didactic decisions made by teachers. This paper shifts focus from our previous publication, where we described the technical implementation of a RAG system and its educational applications in university teaching. Here, we address the systemic requirements necessary for effectively using RAGs in schools.

Based on existing empirical research on the use of chatbots in the classroom, we first **identify barriers** to their use in schools and **derive systemic requirements**. We illustrate the benefits of the RAG concept and emphasize how it can lower these barriers. In a second step, we present **existing solutions for the use of RAG systems in schools** and categorize these tools according to our identified requirements. We show that existing options fail to consistently lower the barriers. Based on this analysis, we present a **locally hosted open-source low-code RAG system template**, which tech-savvy teachers can replicate and implement in the classroom after a brief introduction. Our aim is to empower teachers to actively shape the future of education with AI technologies instead of passively using chatbots with opaque architectures and fixed knowledge bases that cannot be adapted to the curriculum.

We are collaborating with teachers in a **Professional Learning Community** (PLC), which brings together secondary school teachers of all subjects. In the virtual meetings of the PLC, we work together on several bots. Aside from this, the PLC is a platform for teachers to exchange didactic ideas on the use of chatbots in the classroom. The PLC teachers act as multipliers, passing on their newly acquired knowledge about RAG systems in general and about our RAG system template in particular to colleagues at their schools. We will discuss our experiences of the PLC, along with key **lessons learned**.

II. Classroom Requirements for Chatbots

Research on generative AI in schools is currently proliferating, making an all-encompassing overview of research impossible. With the aim of identifying requirements for the use of chatbots in the classroom, we focus on the use of chatbots by students. Other applications of AI in schools, e.g. for lesson preparation, assessment, or administrative purposes, are not relevant to this work.

The use of chatbots in the classroom offers numerous opportunities for students. For example, chatbots can supplement the teacher's feedback like automated tutoring systems supporting self-directed learning [4]. To ensure that the use of chatbots in schools can achieve the desired positive effects, requirements in several areas must be met. We derive various requirements from the existing empirical research on the use of chatbots in the classroom and group them into four categories. Drawing on the experiences of teachers in our PLC, we examine these

Author's version of the publication:
S. Martin, A.-M. Lauber, and B. Pampel, "Let's Chat about This - A Template for Well-Aligned AI Integration in Schools",
2025 IEEE 4th German Education Conference (GECon), Hamburg, Germany, 2025, to appear.

identified barriers to assess whether the list is complete or if additional challenges exist.

A. Legal Requirements

The most important legal requirement for the use of chatbots in schools is data privacy. Commercial systems that require registration pose challenges for teachers when implementing them in educational settings due to privacy regulations (e.g., increased organizational effort, as parental or guardian consent is required for underage students if personal data is processed for registration), especially in schools without an established institutional framework for AI chatbot use, where responsibility rests solely with the teacher. Therefore, systems should be designed to operate **without mandatory registration** L1 for the students. The use of commercial LLMs in education raises additional concerns regarding **data privacy and security** L2 , as user inputs are typically processed and stored [4], [5]. Therefore, it is crucial for teachers to understand how input data is handled [6]. Ideally, systems used in schools should be self-hosted or operated within a trusted environment without data analysis or storage, or, at the very least, provide transparent and clear information on data processing and storage practices [5]. Copyright issues are another legal requirement. However, they typically arise only when chatbot-generated texts are submitted as original work (e.g., in assignments) without prior agreements clarifying the use of AI-generated content or in case a text is subsequently published in some form.

B. Availability Requirements

In terms of the availability of the chatbot, **scalability** A1 and **cost requirements** A2 must be met in order for the chatbot to be used in the classroom. Schools do not usually have a generous budget for hardware and software. Therefore, chatbot systems should be available at little to no cost and should not require extensive technical support, keeping the maintenance costs low. Furthermore, these systems must be scalable to accommodate the entire class. Free options are typically financed through data processing, making them difficult to use in educational settings due to privacy concerns. The fees for commercial options but also maintenance costs of self-hosted options can pose a challenge for schools [5]. Further funding for technology support would be desirable [7], but teachers cannot wait for a political change in education; they must be able to act independently.

C. Personal Requirements

At the personal level of the individual teacher, numerous variables can influence whether chatbots are used in the classroom. First of all, chatbot systems should be **transparent** P1 so that teachers can understand how they work [8]. This is because integrating LLMs into effective teaching requires understanding their functionalities, capabilities, and limitations [5].

In addition, the technology should be viewed as **useful** P2 and **easy to use** P3 , **provide support** P4 , and minimize perceived risks. These factors contribute to the intention to use. In order to assess whether a person will use a new technology, the Technology Acceptance Model (TAM, [9]) with its various extensions is a common approach. TAM has also already been used in combination with the UTAUT-Model (Unified Theory of Acceptance and Use of Technology, [10]) investigating the **intention to use** generative AI [4]. According to TAM, the intention to use is affected on the one hand by the Perceived Usefulness and on the other hand by the Perceived Ease of Use [9]. **Perceived Usefulness** refers to the belief that adopting a particular technological system will be beneficial. The greater the Perceived Usefulness of a technology, the more likely it is to be adopted and utilized. Another factor is the **Perceived Ease of Use**, which describes the extent to which one believes that handling a new technology can be learned in a reasonable amount of time and effort [9]. **Facilitating conditions** including the degree to which one believes that there will be technological support for a system can influence the Perceived Ease of Use. **Perceived Risk** is the perception that adopting a technology may also have negative outcomes. As the Perceived Risk increases when using a technology, the intention to use that technology will decrease. This fear of risk may amplify other barriers [7], hence it is taken into account in connection with these other barriers and requirements.

D. Integration Requirements

When interviewing teachers, one of the biggest concerns is the **misuse of chatbots** I1 by students [8]. The effortlessly generated information could undermine critical thinking and problem-solving skills [11]–[13] by preventing a deeper engagement with the learning content [14]. By simplifying the acquisition of answers, systems may lead to distorted self-perception of their own skills and may diminish learners' motivation to conduct independent investigations, skipping their real knowledge gain in finding own solutions [5], [6]. In the best case, we can prevent misuse from the outset by optimizing systems for the intended task and restricting them from providing any additional information. Even if the generated content can be restricted, the chatbot could be persuaded into discussing topics it isn't supposed to and making statements it shouldn't (*prompt injection*, [15]). Therefore, systems should enable reliable customization of the chatbot's role, context, and permissible information while restricting unauthorized content.

The **reliability of the generated information** I2 is a crucial factor when working with generative AI. If a system provides incorrect information or guidance, it could mislead students and hinder their learning progress [6]. Results displaying the same imbalances as the training data can negatively influence teaching and learning (e.g. social biases). Another problem is that utterances may include plausible hallucinations [16], which are ideas and information that initially seem to make sense but later are discovered to be incongruous [16], [17], posing a trap for students.

The use of AI systems in schools has to be embedded in the curriculum and in didactic considerations in a manner that complements and enhances the learning experience, instead

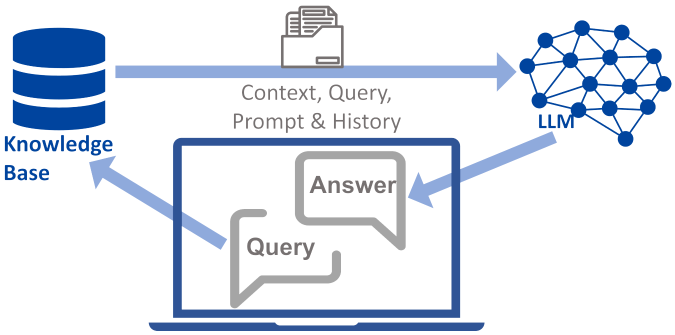

Fig. 1. Simplified represantation of RAG's funtionalities.

of replacing it [5]. Chatbots must therefore be able to **flexibly adapt to didactic settings and curricula** (I3). LLMs mostly struggle to adapt to the diverse needs of students and teachers and may lack the level of adaptability necessary for effective learning and teaching [5]. For instance, the training data of the system may be outdated and/or at an inappropriate level of detail or complexity [16] leading to responses that are hard to align with the ideas or plans of teachers. Aligning concepts and lesson plans with system-generated outputs is time-consuming and complex, as responses are not reproducible. This makes lesson planning with such systems challenging and introduces a certain degree of uncertainty. Therefore, systems, especially their knowledge bases, should be adjustable to meet the specific needs of teachers. The crucial point here is that only the teacher, and not the students, creates the knowledge base and decides on its completeness and correctness.

III. Towards a Solution: RAG Systems

Figure 1 shows a simplified representation of a RAG [2]. When a user submits a query, it is first compared with the information stored in a knowledge base relevant to the specific use case. This information is processed into smaller snippets, which can be retrieved by specialized LLMs as needed [18]. The LLM then receives the query, the pertinent contextual data, and the system prompt, ensuring that its role is limited to structuring and articulating the provided information coherently, rather than generating content beyond the predefined knowledge scope.

RAG can significantly lower the integration barrier, effectivly prohibiting misuse (I1) by providing a system prompt, which explicitly defines the system's preliminaries, limitations, and context. RAGs are also less susceptible to malicious queries, such as prompt injection. Limiting information to up-to-date information with appropriate detail minimizes hallucinations and makes the system reliable (I2). Further, RAG enhances contextual coherence and adaptability (I3), constraining responses to verified information from a provided knowledgebase [18].

IV. Outline of Commercial Solutions for the Use of RAG Systems in Schools

RAG systems appear to be suitable for fulfilling many requirements for chatbots used by students that were identified in section II. There are already several commercial providers of RAG chatbots, so the question is whether one of these systems is suitable for use in the classroom. In our previous work, we provided an extensive overview of the state of research and projects featuring RAG systems in education [3] (see also [19]). Several RAG-based chatbot prototypes have been developed for higher education, with positive feedback on their potential as teaching aids. However, most systems, including OwlMentor [20] and CS50 Duck [21], lack adaptability to different courses. While these systems show promise, they rely on costly models (GPT-3.5 Turbo and GPT-4) and are tailored to specific courses, requiring technical expertise to replicate. In this analysis, we want to focus on chatbots that on the one hand are available to teachers and on the other hand enable teachers to make changes to the backend (e.g. knowledge base; cf. Table I).

Custom GPT [22]: Several online platforms offer no-code chatbots, primarily designed for companies to use on their websites. These platforms allow users to upload their own material and define a system prompt. However, such systems tend to be expensive and are not well-suited for use in schools due to privacy compliance issues and difficulties in sharing with the entire class. For example, Custom GPT offers some level of customization, but control over the chatbot's behavior is limited, and its usage is costly. In our tests, we were able to easily steer the chatbot away from its predefined knowledge base, trigger hallucinations, and exploit vulnerabilities such as prompt injection.

Fobizz [23]: Fobizz is a costly online platform, which offers alongside other features a RAG-based, privacy-compliant chatbot that can be set up by the teacher and shared easily with classes without student registration. Fobizz uses a variety of LLMs, allowing the inclusion of system prompts, documents, and initial messages. Unfortunately, we were able to easily lead chatbots astray, causing them to hallucinate, even when using a very rigid and well-tested system prompt.

EduBot [24]: EduBot is a costly teaching platform. Despite being based on GPT-4 or GPT-4.0 Mini, EduBot is fully privacy-compliant and tailored specifically for use in schools. It is easy to share created bots with the whole class, and the system prompt as well as an initial message can be customized. However, we were able to easily lead the chatbots away from the document, causing them to hallucinate, even when we were using a rigid and well-tested system prompt.

ChatPDF [25]: There are a number of options to allow users to chat with PDFs, for example ChatPDF. It enables users to interact with any PDF document by asking questions and receiving answers without requiring registration. Teachers do not have any control over the usage of the chatbot, since the students have to set up the bot themselves. We were able to easily lead the chatbot away from the document, causing it to hallucinate.

fAIrChat [26]: fAIrChat is an AI-powered chatbot integrated into the Moodle learning platform. The project was initiated by the Ministry of Education, Youth and

	legal		available		personal				integration		
	no registration (L1)	data privacy (L2)	scalability (A1)	low costs (A2)	transparent (P1)	usefull (P2)	ease of use (P3)	support (P4)	no missuse (I1)	reliability (I2)	adaptability (I3)
Custom GPT	○	○	●	○	○	●	●	◐	◐	◐	●
Fobizz	●	●	●	○	○	●	●	●	◐	◐	●
EduBot	●	●	●	○	○	●	●	●	◐	◐	●
ChatPDF	●	○	◐	●	○	◐	●	○	○	○	●
fAIrChat	?	●	●	○	○	?	?	?	○	○	○
our RAG template	●	●	●	◐	●	●	◐	●	●	●	●

○ not given - ◐ partely given - ● given - ? unknown

TABLE I
COMPARING EXISTING SOLUTIONS FOR THE USE OF RAG SYSTEMS IN SCHOOLS WITH OUR RAG SYSTEM TEMPLATE.

Sports Baden-Wuerttemberg to provide students with privacy-compliant access to generative language models like GPT. However, the application is still in the testing phase and is not accessible to teachers unless they are part of the test schools. Additionally, it is unclear whether fAIrChat offers the option to create custom bots. As of now, we are unable to test it.

In summary, none of the commercial solutions come close to fulfilling the requirements we have identified for the use of chatbots in the classroom (cf. Table I). Most RAG systems presented require paid subscriptions (A2), in some cases even registrations for students (L1) and unclear malicious data privacy regulations (L2). School legislation and the financial resources available to schools, therefore, already exclude many of these tools. At the individual teacher level it is above all the lack of transparency (P1) that makes the tools problematic. These tools only offer text fields for system prompts and buttons for file uploads. As a result, the structure and functionality of these systems remain completely hidden for the teachers. They cannot understand the logic used by the chatbot to generate answers and therefore cannot check its reliability systematically. We managed to get all the tools in the test to deviate from their predefined knowledge base (I1) and tempt them to hallucinate (I2). This is probably because those RAG chatbots store additional hidden system prompts, which are hierarchically higher than the system prompts provided by the teacher.

The difficulties we identified with commercial RAG chatbots were confirmed by the teachers in our PLC. When using such chatbots in the classroom, they are particularly concerned about data privacy (e.g. if students have to create their own account). Teachers also reported that their students were unable to recognize errors in the answers provided by commercial chatbots (e.g. Fobizz). It is also problematic for didactic embedding in lessons if the knowledge base of the chatbot cannot be adapted to the curriculum and the specific content of the lesson (e.g. textbook).

V. Development of an Open-Source Low-Code RAG System Template

By creating their own RAG system, teachers have more control over how and to what extent they can support their students' learning. However, developing such a system from scratch, including the direct interaction with LLMs, requires expertise in programming, API integration, and managing computational resources, making it unrealistic for the majority of teachers to independently realize. The implementation can be simplified using the Python library LangChain [27] with high-level abstractions and prebuilt components. However, LangChain still requires programming knowledge for effective use. Flowise [28] is an open-source, low-code tool based on LangChain that allows teachers to create customized LLM workflows through a drag-and-drop interface. While this simplifies the process, basic technical knowledge is still needed for tasks like API configuration and workflow optimization. But with expert guidance, tech-savvy teachers can effectively use Flowise to create RAG systems.

We will outline the tasks teachers have to complete. First, they need access to LLMs, with any LLM being suitable. However, we recommend open-source options like LLaMA, which can be hosted locally. Alternatively, LLMs hosted by trustworthy, data-secure platforms can be used. During this research phase, we utilize LLMs hosted by Chat AI [29], provided by the Gesellschaft für wissenschaftliche Datenverarbeitung mbH Göttingen (GDWG). These LLMs run on scalable, high-performance computing systems with secure cloud access and do not store or use any user data. Additionally, Flowise must be installed on the system.

Teachers can use the Flowise template to implement the RAG system we designed (cf. Figure 2). Following the structure of RAGs the template can be divided into three phases:

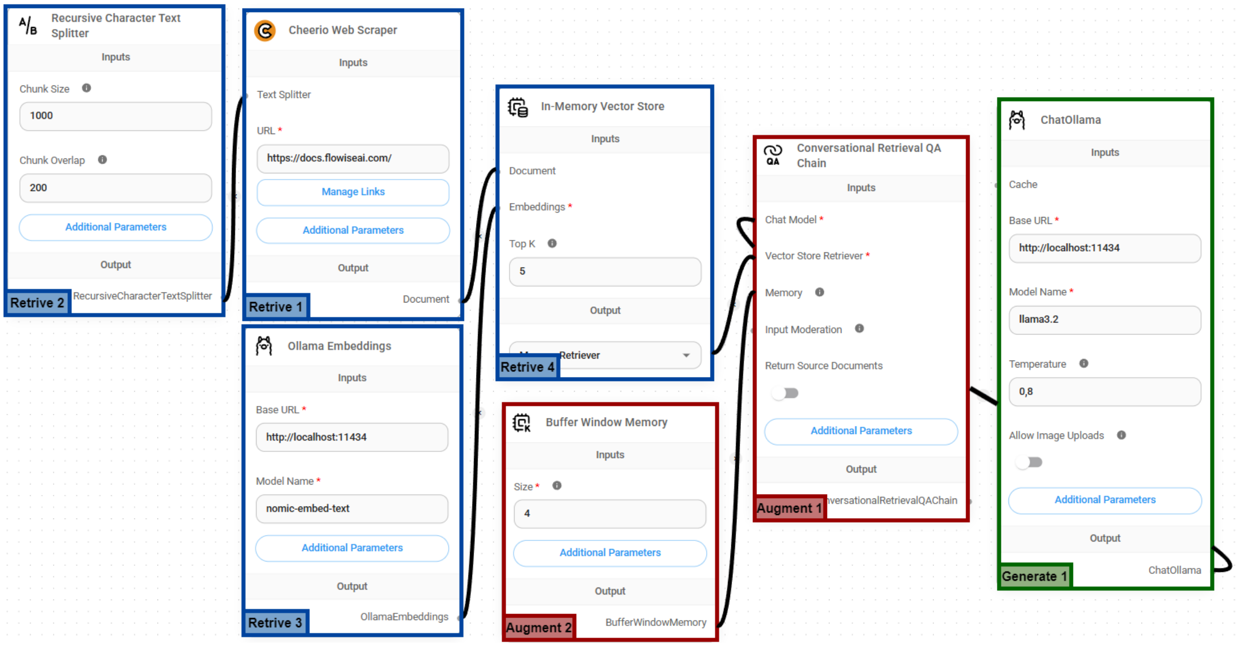

Fig. 2. Flowise template for the implementation of a RAG system.

retrive, **augment** and **generate**. During the **retrieve** phase, information from the knowledge base is efficiently made accessible to the system. Therefore, we can import information from external sources, such as websites, using a **Web Scraper** *(Retrive 1)* that extracts text from the website and its subpages. To use information, pre-processing is required. The text is extracted from the source and divided into chunks using a **Text Splitter** *(Retrive 2)*. To make the text more accessible and easier to retrieve when searching for relevant information, embeddings are created for these chunks. The **Embeddings** *(Retrive 3)* generate high-dimensional numerical vectors that capture semantic and contextual information, enabling a search for semantic similarities instead of only searching for matching keywords. These vectors are stored in a **Vector Store** *(Retrive 4)* knowledge base.

In the **augment** phase, we aggregate relevant information. The core component of the augment is the **Conversational Retrieval QA Chain** *(Augment 1)*. Chains link inputs, like user queries, to outputs, such as responses or retrieved information. The Conversational Retrieval QA Chain, for example, integrates conversation history with external knowledge retrieval and a prompt. For each query, the Conversational Retrieval Chain retrieves the most relevant information chunks based on the stored embeddings from the Vector Store. To maintain context, information is retrieved from the **Buffer Memory** *(Augment 2)*, which stores the conversation history. A parameter determines how many of the last messages are used, preventing the prompt from being overwritten by an excessively large conversation history.

In the **generate** phase, the chosen **LLM** *(Generate 1)* uses the retrieved information chunks, the conversation history, the query, and the system prompt to generate accurate responses.

The last step in the process is the interaction between the user interface and the backend. A simple solution involves hosting a basic website provided by Flowise on the local network, enabling teachers to easily share the chatbot in the classroom. Students do not need to log in, and teachers can evaluate chats anonymously.

VI. Discussion and Lessons Learned

The use of our proposed RAG system template can provide several benefits for teachers. It fulfills legal requirements because it does not require student registration (L1), and data is stored securely (L2) on the teacher's system or a trusted LLM host that complies with privacy regulations. It should be noted, however, that teachers do not always have access to a data-secure LLM or a system with enough computing power to host a smoothly running LLM. The teachers in our Professional Learning Community (PLC) have access to the GWDG's data-secure LLM and can therefore fulfill this requirement with their RAG systems. It's also available to entire classes at no cost (A2), if it is locally hosted on the teacher's system or a school server and shared on the local network. Our RAG system template performs well in terms of personal requirements. Provided that a suitable LLM is used, the main advantage is the transparency (P1) : Because the teachers implement the chatbot themselves, they have full control over the functionality and parameters of the RAG chatbot. This allows teachers to learn about the fundamentals of the RAG technology, emphasizing process knowledge over application knowledge. By focusing on underlying methodologies, teachers can adapt to needs more flexibly, fostering critical thinking and long-term learning. Although the technical setup may be a bit more complex and requires some guidance, this approach is more sustainable than using pre-made tools. Unlike other systems, this approach minimizes misuse I1 by relying solely on system prompts set by the teacher. In contrast, commercial RAG chatbots apply hidden higher-level system prompts that tamper with user inputs, easily causing manipulation and triggering hallucinations. In addition, the adaptability I3 of such a system to the content and the didactic requirements of the lesson is particularly important. This is fully achieved with our RAG system template, as the knowledge base is defined by the teacher and the chatbot's behavior can also be restricted.

As described above, we have founded a PLC to test our RAG system template and multiply it into schools. In the virtual sessions of the PLC, teachers are not only enabled to implement our RAG system template, but are also given a platform to exchange didactic ideas on the use of chatbots in the classroom. We document the discussions in the meetings with the consent of the participants for our research and for developing our RAG system template.

At the first PLC meeting, we presented our RAG system template and its implementation to the teachers. In the subsequent online survey, the majority of the teachers surveyed were in favor of such a system being implemented by (tech-savvy) teachers (N = 7, MW = 4.4; SD = 1.1; 5-Point-Likert-Scale). A clear majority believes that such a RAG system can be used appropriately in the classroom (N = 7, MW = 4.0; SD = 1.0; 5-Point-Likert-Scale). In the discussion, the use of the system as a learning partner for self-directed learning or for catching up on missed lessons was mentioned, for example. After the first meeting, the teachers were given time to implement a RAG system according to our instructions.

The second PLC meeting focused on optimizing the RAG system. The teachers also discussed the advantages of our RAG system template compared to commercial solutions. Drawing on their own experience with chatbots in the classroom, the teachers emphasized the possibility of our RAG system template to restrict the answers of the chatbot by the teacher. For example, a chatbot in a math lesson can be prohibited from making calculations the students should do themselves so that it can only provide help and tips. The chatbot can also be restricted from hallucinating, i.e. inventing answers, if there is no suitable content in the knowledge base.

Our experience from the PLC shows that teachers are able to implement a RAG chatbot according to our template and use it in the classroom. We have had the same experience with our RAG system template in the university context [3]. A decisive positive side effect is the fact that teachers can better understand how chatbots and RAG systems work by implementing them self-reliantly. This incidentally acquired knowledge helps teachers in utilizing AI in general.

VII. Conclusion and Future Work

We have shown that the use of chatbots in the classroom is not trivial but rather associated with numerous barriers. We have identified requirements for chatbot systems that must be met in order for them to be used profitably in schools. Our experience and previous research show that RAG systems can fulfill these diverse requirements [3]. However, an analysis of available RAG systems for the classroom demonstrates that commercial chatbots cannot fully and adequately exploit these advantages of RAG systems, which raises problems for their use in the classroom. With our locally hosted, open source, low-code RAG system template, we have presented a way in which tech-savvy teachers can be empowered to use their self-created bots without relying on expensive and potentially risky tools. This approach allows teachers to harness the full potential of AI and develop their tool themselves. The feedback from our PLC is promising and shows the potential of our development. The teachers in the PLC serve as multipliers who carry the idea of the self-built RAG chatbot into the schools. It would be desirable for this multiplier effect to increase in the future and for the RAG chatbots to be integrated into a wide variety of teaching scenarios using our template. In this way, very different didactic ideas could be tested. At the moment, we are working on more advanced templates for our RAG system template, for example, to explicitly prohibit the system from answering questions, which come from exercise sheets or exams. Due to our work with the PLC, we have also learned about the added value of implementing one's own RAG chatbot in terms of teachers' process knowledge about AI and RAG systems. In our experience, it would be desirable for education policy to provide more support for projects that train process knowledge rather than application knowledge.

VIII. Acknowledgements

This work was partially funded by the Federal Ministry of Education and Research, project "MINT-ProNeD", grant number 01JA23M02K. We want to thank the Ministry of Education, Youth and Sports Baden-Wuerttemberg and the Center for School Quality and Teacher Education Baden-Wuerttemberg for their financial support and close collaboration in developing the Kontaktstudium IMP/Informatik. We also thank the GWDG for the possibility to use the Chat AI services for our research.

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