Supporting Children's Information Discovery Tasks in Education: A Preliminary Exploration on the Use of ChatGPT

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ABSTRACT

The influence of ChatGPT and similar generative models on education is being increasingly discussed. With the current level of trust and enthusiasm among users, ChatGPT is envisioned as having great potential. As generative models are unpredictable in their ability to produce biased, harmful, and unsafe content, we argue that they should be comprehensively tested for more vulnerable groups, such as children, to understand what role they can play and what training and supervision are necessary. In this paper, we present the results of a preliminary exploration of the use of ChatGPT in educational settings to support *children* in completing *information discovery tasks*. We analyze ChatGPT responses using a variety of lenses to discern the effect of interacting with ChatGPT, its challenges, and its limitations. We discuss research gaps the information retrieval community can address in collaboration with the NLP, AI, and education communities.

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1 INTRODUCTION

We are witnessing the ever-growing development and interest in large language models (LLMs) and how they can be used to address information-seeking tasks. From designing AI-powered bots such as ChatGPT[1] and YouChat[2], to model-based retrieval models [27], generative AI has attracted increasing attention in the community.

ChatGPT is here; researchers, practitioners, and everyday users alike are aware of it, yet all are still trying to understand the audiences, tasks, and contexts in which ChatGPT may be useful [30]. Emerging technologies like ChatGPT provide "opportunities for an active and meaningful learning environment in the school context, provoking important reflections on what is expected from the 21st-century school" [32]. Indeed, early adopters in this context have begun integrating ChatGPT in their schools, focusing on the potential benefits it can bring to improve teaching and learning quality, as well as personalize the learning experience [20]. At the same time, there are already concerns about the instrument itself and its likely misuse [3]. Moreover, model bias [26, 35] and hallucination [19] are two well-known problems of generative models which can affect all groups of users but would be harder for young users to detect and combat it. As shown in the literature [24, 28, 29], children tend to trust a system more easily which can lead to unwanted results when a system like ChatGPT does not behave as intended.

The educational context encompasses many teaching and learning tasks that AI technologies could enable. It serves a wide range of individuals; from educators themselves to students of all ages. We argue that with the rapid and ever-changing landscape of AI technologies for the educational context; it is critical to identify *how we can explore and assess the impact AI technologies can have in the educational context, and if so, what are the advantages and inevitable challenges ahead?* To start answering this question, we define the scope of this work following the framework introduced by Landoni et al. [21], which guides the design and assessment of information retrieval technology through four pillars. In our case, these pillars are children aged 10–11 (4^{th} grade in primary school) as the *user group*, classrooms as the *environment*, information discovery as the *task*, and information produced by ChatGPT as the *strategy*. Specifically, we conduct a preliminary *quantitative and qualitative exploration* to examine responses generated by ChatGPT for a number of prompts common to the 4^{th} grade history curriculum from different lenses, including readability, language, and type of tasks.

Findings reveal that ChatGPT could support children's information discovery, even if the formal assessment of readability–in agreement with direct feedback from children–shows that responses are more complex than required for this age group. Misinformation, however, is mixed in ChatGPT responses in such a close manner that is really difficult for children to spot. Hence the need to warn teachers and train children to be critical when assessing ChatGPT answers and possibly verifying sources. In the end, there are "significant risks when using ChatGPT as a source of information and advice for safety-related issues" [30]. With this work, we build on this discourse by exploring the risk and opportunities of using ChatGPT as a source of information to support the classroom.

2 EXPERIMENTAL SETUP

Prompt design. To gather data for analysis, we adopt the prompts introduced in [5]–defined by expert educators to guide the completion of an online inquiry assignment in the 4^{th}. Specifically, we rely on twelve questions related to Ancient Rome, a history topic

Table 1: Sample prompts (translated from Italian).

ID	Question	Category
1	Why did the first Romans settle on the hills?	Information discovery (in P_{ID})
2	Were the kings of Rome chosen by birth or by election?	Fact-finding (in P_{ID})
3	How long did the monarchy last?	Multi-step (in P_{ID})
4	Who was King Tarquinius the Pisquano?	Fact-finding (in P_H)

[1] https://chat.openai.com/
[2] https://you.com/

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common in the school curriculum (P_{ID}). As generative LLMs are affected by '*hallucinations*', i.e., they are "prone to hallucinate unintended text, which degrades the system performance and fails to meet user expectations in many real-world scenarios" [19], we ask an expert educator to define three prompts aligned with Ancient Rome but referring to fictional historical events/figures (P_H) to enable appraisal of ChatGPT's ability to support inquiry assignments.

Language dependency. To examine variability in ChatGPT's performance due to language, we turn to native speakers to translate P_{ID} and P_H from their original Italian to English.

Prompt categories. We categorize prompts as in [5, 21] based on the type of task and interactions they elicit: (i) *fact-finding* are straight-forward prompts that require a precise answer; (ii) *information discovery* are open prompts that require a short textual description as an answer; and (iii) *multi-step* are complex prompts that require connecting information to find an answer. By considering varied task categories, we can examine ChatGPT's behavior when faced with prompts of increased complexity (see Table 1).

Data collection. We use two strategies: (i) $ChatGPT_D$ where we elicit ChatGPT responses for P_{ID} and P_H; and (ii) $ChatGPT_{CF}$ where we add the phrase "explained to a fourth grader" (in the respective language) to P_{ID} and P_H. We posit that including an explicit target audience could yield child-friendly responses, fitting the target audience under study. This results in 60 text samples, i.e., responses, uniformly distributed across language and collection strategy.

Exploration We probe the responses generated by ChatGPT using eight measures that capture the *linguistic and stylistic complexity* of ChatGPT responses. For this, we use Python's `textstat` [2] and `textcomplexity` [1], with provide options for Italian and English. In particular, we analyze the generated results in terms of (i) word count; (ii) unique word count; (iii) sentence cont; (iv) average sentence length; (v) Flesh Reading Ease [16]; (vi) reading time [12]; (vii) entropy [34]; (viii) closeness []; and (ix) readability score given by the students. When juxtaposing results across response generation strategies, prompt type, i.e., P_{ID} and P_H, prompt categorization, and language, we determine significance using t-test, $p < 0.05$.

We also gauge the *suitability* of ChatGPT responses for the main stakeholders in the educational context under study: children. For this, we turn to 55 students in the 4^{th} grade of a primary school in Italy[3]. We share each response generated by $ChatGPT_{CF}$ for P_{ID} and ask them to "Rate the readability of this text." Using a 5-point Likert scale, where 1 indicates very difficult to comprehend and 5 very easy, we rely on emojis for feedback elicitation–a common practice when involving young users [33].

3 RESULTS, DISCUSSION, AND IMPLICATIONS

Here, we present the results of our initial exploration of ChatGPT.

Can ChatGPT adapt its responses to primary school students? We examine differences in linguistic and stylistic complexity measures inferred from responses generated by $ChatGPT_D$ and $ChatGPT_{CF}$ for P_{ID} in their original Italian. As shown in Fig. 1a, the average number of words significantly decreases for $ChatGPT_{CF}$ responses compared to $ChatGPT_D$. The same is true for the average sentence length and average reading time (the estimated amount of time it takes to read a given text). At the same time, the average number of sentences per response significantly increases for $ChatGPT_{CF}$, when compared to $ChatGPT_D$; we see this as an expected trade-off to produce shorter, easier-to-read sentences. On average, the number of unique words is comparable across strategies. Yet, it emerges from Fig. 1a that $ChatGPT_D$ responses result in a wider range of unique words.

Flesh Reading Ease scores, which determine the degree of difficulty of text samples, significantly decrease from an average score of 70 to less than 60 for responses generated using $ChatGPT_{CF}$ and $ChatGPT_D$, respectively. Scores of 70 and above indicate fairly easy-to-read text, whereas scores of '60-69' and '50-59' signal standard and fairly difficult-to-read texts, respectively. The mean entropy of $ChatGPT_{CF}$ responses is lower than $ChatGPT_D$ (Fig. 2a). This difference indicates that $ChatGPT_{CF}$ is more likely to predict correct terms and is therefore more certain than $ChatGPT_D$ in generating responses. In addition, the mean closeness of responses generated by $ChatGPT_{CF}$ is higher than $ChatGPT_D$. The closeness metric is inversely correlated to the average length of the shortest path between nodes of the dependency tree. Hence, the generated responses for children are less complex than $ChatGPT_D$ in terms of dependency between terms in a sentence.

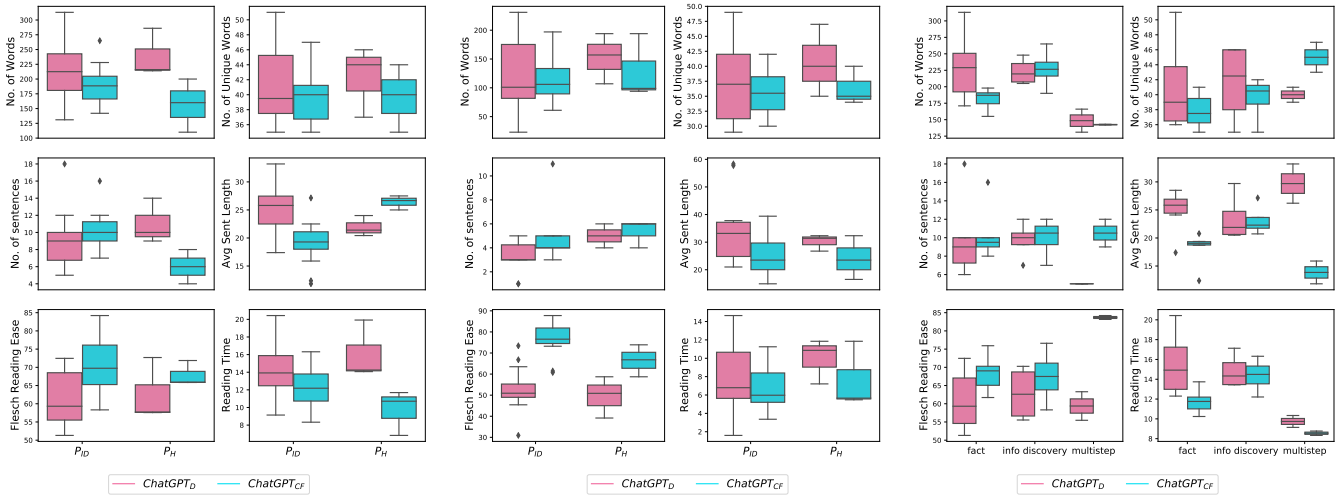
From these results, we can infer that when explicitly specifying the target audience, ChatGPT adapts its responses to produce easier-to-decode [11] responses with a more limited vocabulary and shorter and simpler sentences. Outcomes match those reported by Benzon [9] who states that "ChatGPT can adjust its level of discourse to accommodate children of various ages." It is important to note, however, that text samples scored in the '70-79' range of Flesh Reading Ease reflect material suitable for 7^{th} graders (i.e., 13 to 14-year-olds). This is a limitation, as responses are meant to match the reading abilities of 4^{th} graders.

We assess ChatGPT's versatility when addressing prompts for different inquiry tasks. From Fig. 1c and 2c, we detect that except for entropy and closeness, trends reported thus far are not consistent across categories for P_{ID}. They are in line with those observed for fact-finding prompts but seldom coincide with those emerging from information discovery and multi-step prompts. We attribute this to the nature of the tasks and their growing complexity.

Does ChatGPT hallucinate in response to fictional prompts? To scrutinize ChatGPT's reactions to prompts referring to fictional historical figures and events related to Ancient Rome, we compare linguistic and stylistic complexity measures computed for P_{ID} vs. P_H. It is visible from Fig. 1a that scores computed for P_{ID} rarely match those for P_H. Among salient differences, we highlight a significant increase in average sentence length as well as a decrease in the average number of sentences and average reading time for response generated by $ChatGPT_{CF}$ when compared to $ChatGPT_D$.

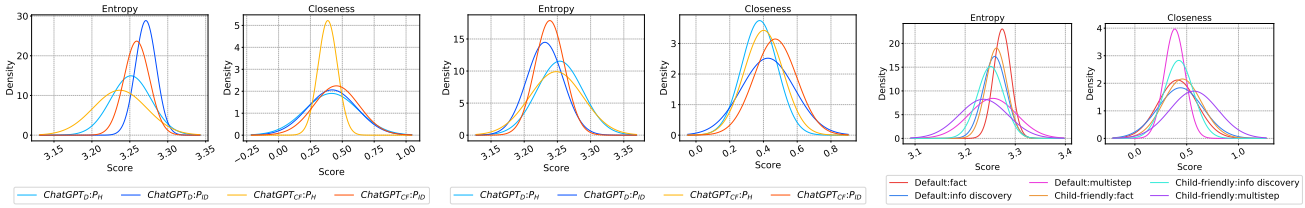
We recognize an interesting pattern via examination of responses to P_H: regardless of the strategy used for response generation, for 2 out of the 3 prompts, ChatGPT seems to presume that the user make a typo on the historical figure/event mentioned in the prompt. Accordingly, its responses do not address the intent of the prompt. On the other prompt, ChatGPT states that it does not recognize the existence of a particular historical event/figure, and proceeds to

[3]Required ethical considerations were accounted for in this data collection process.



(a) Italian (b) English (c) Italian by task category

Figure 1: Overview of text-based measures computed on responses generated by ChatGPT



(a) Italian (b) English (c) Italian by task category

Figure 2: Closeness and Entropy of ChatGPT responses.

discuss a similarly-named event. These findings further showcase issues of hallucinations impacting generative models. We argue that this is a concern for the audience of this study, who seldom question the veracity of the online information presented to them [24].

Are ChatGPT responses useful to primary school students? We examine the responses provided by 4^{th} grade students regarding their ability to understand $ChatGPT_{CF}$-generated text–a proxy that enables us to judge the perceived fit of ChatGPT.

The distribution captured in Fig. 3 points to children placing the readability of most prompts between neutral and good (i.e., neutral and Happy in terms of emojis). The responses to the two prompts deemed the most readable (5 and 10) were relatively short and in the case of prompt 10, the response was a short story about a legend in ancient Rome, which children are used to and contained less specific lexicon. Agreeing with the discussion on readability scores presented earlier, the samples produced by $ChatGPT_{CF}$ appear too complex for a complete understanding by a 4^{th} grader. Overall, we surmise that children understood the samples presented to them, but were not completely satisfied; suggesting in turn that ChatGPT is not quite ready to really help children.

Does language affect ChatGPT's ability to adapt its responses to primary school students? For tasks like sentence understanding, ChatGPT fares better for English-written text, as opposed to other languages [8]. This is why we look for possible discrepancies in scores estimated from responses for P_{ID} in Italian vs. English.

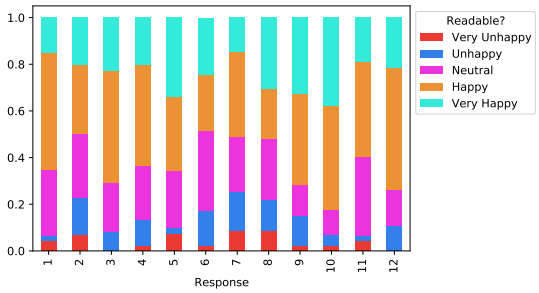


Figure 3: Children's perceptions on the ease of comprehension of $ChatGPT_{CF}$ responses to P_{ID}.

Contrasting Fig. 1a and 2a with Fig. 1b and 2b, we notice how trends and significant differences in scores observed for $ChatGPT_D$ vs. $ChatGPT_{CF}$ remain the same regardless of the language.

As seen from the analysis of the responses for P_{ID} in Italian, those produced using $ChatGPT_{CF}$ for prompts written in English yield significantly higher Flesh Reading Ease scores i.e., easier to read, than those using $ChatGPT_D$. The average score of responses produced using $ChatGPT_D$ are closer to 50, i.e., 'fairly difficult' to read, whereas those generated by $ChatGPT_{CF}$ are closer to 75 (and above), i.e., 'fairly easy.' The average reading time significantly increases (significantly decreases, resp.) for responses produced by $ChatGPT_D$ ($ChatGPT_{CF}$, resp.) for English prompts with respect to their Italian counterparts. These results indicate that, while still

above the skills of 4^{th} graders, ChatGPT is more likely to provide simpler text in English than in Italian. This is anticipated, given ChatGPT's self-proclaimed preference for English (Fig. 4). Regarding closeness, the generated responses in English follow the same trend as in Italian; with the difference between the closeness of the responses generated by $ChatGPT_{CF}$ and $ChatGPT_{D}$ being more prominent in English. For both $ChatGPT_{D}$ and $ChatGPT_{CF}$ the mean entropy of responses for P_{ID} is lower than P_H, which indicates that chatGPT is more confident in generating the response for P_{ID} than P_H, a promising feature when considering how important it is to prevent children's exposure to information pollution.

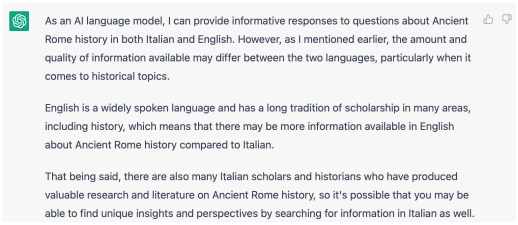


Figure 4: ChatGPT and its preference for English.

Could ChatGPT replace web search in the primary school? Haque et al. [17] question whether ChatGPT could replace search engines, as it presents "information conveniently by selecting the most appropriate information and explaining it in simple terms." Neither ChatGPT nor web search engines were designed specifically for the educational context. Web search engines, however, are the go-to portals to resources that can enable teaching and learning in formal and informal settings [7, 15, 23, 25, 36]. They are embedded in the educational context, even when their limitations to retrieve and prioritize educational resources are well documented [6, 31]. As a generative model, ChatGPT will not always produce reliable responses, in turn exposing children to information pollution. Literature also reports that children struggle with formulating effective queries and identifying relevant resources among those in SERP when seeking online resources to support inquiry tasks in the education context [7]. Therefore, it is natural to assess the applicability of ChatGPT as a conduit for information discovery.

Informed by the results discussed thus far, ChatGPT could ease query formulation: directly using assignment prompts, students can access complete answers. This could be to detriment of developing a skill–query formulation–required in the digital ecosystem we inhabit. ChatGPT also removes the need for SERP exploration by providing direct responses and hiding sources under a smoothly written piece of text ready to be used, with no more access to indirect clues of their quality as found in SERP. Still, with children seldom questioning source reliability [24], what are the consequences of ChatGPT hallucinations? Web search engines and ChatGPT are examples of technologies made for general audiences that can therefore make generalizations and misinterpret users' needs[13, 14]. In this case, what are the implications for the educational context when ChatGPT generates incorrect responses that do not necessarily match the intent expressed in the prompt used to elicit a response? Presenting younger user groups with material suitable for their skills is a challenge for web search engines and ChatGPT. The average readability level of resources retrieved in response to children's queries is significantly above what they can understand [6, 10]. The same is true for ChatGPT. Recall that the estimated readability of the responses for P_{ID} reflects the skills of 7^{th} graders.

Query formulation impacts retrieval effectiveness and the retrieval of different types of resources [4]. We, therefore, question if variations on prompts used to elicit responses from ChatGPT would result in more (or less) effective responses. A preliminary manual examination of responses produced by modifying the phrase used in $ChatGPT_{CF}$ to elicit child-friendly outcomes indicates that, much like query variations on web search engines, prompt variations influence outcomes. E.g., when asked for advice for a 4^{th} grader on how to prepare a presentation on a school topic about who were the inhabitants of the area where Rome (a variation of one of the prompts in P_{ID}), ChatGPT responded by suggesting how to conduct an online search to gather information, it pointed out online sources that could provide suitable content, and it encouraged using text and images to create engaging presentations. In this case, in lieu of a precise answer, ChatGPT offered scaffolding on how to approach information discovery for the classroom; evincing behavior closer to that of a potential educational agent [22].

4 CONCLUDING REMARKS

AI systems in vogue nowadays, like ChatGPT Google's Bard, and Bing's AI Chat, "trained on unprecedented amounts of data and able to engage in astonishingly diverse conversations" [18] are already used by millions. Yet, we know little about their applicability for specific contexts or their impact on user groups for which they were not explicitly designed. With this work, we aimed to bring attention to the use of AI in education by children. In particular, we discussed lessons learned from a preliminary study of the extent to which ChatGPT can support primary school inquiry assignments, and report on possible advantages and challenges. We used a combination of quantitative and qualitative data to support discussion, by also involving members of the target community to assess the usefulness of available responses to prompts derived from search tasks set by teachers. This approach successfully guided our exploration and grounded it in the classroom.

While limited by the number of prompts, this work showcases the need for further investigations to understand the potential socio-technical implications inherent to the use of generative LLMs in the educational context. We did not repeat response generation multiple times for the same prompt. Yet, there are already indications of how models like ChatGPT dynamically change as they are used. We plan to consider this in future iterations of our work.

ChatGPT has managed to attract a lot of attention, concerns, and even anxiety from educators. We share a more objective account of its potential and limits with the community. Aware of the fact that this technology is here to stay it is worth getting a better understanding of how it can support education and at the same time how to deal with its shortcomings, in order to set the right expectations for all involved stakeholders, starting from children.

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