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Prompt engineering in higher education: a systematic review to help inform curricula

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Abstract

This paper presents a systematic review of the role of prompt engineering during interactions with Generative Artificial Intelligence (GenAI) in Higher Education (HE) to discover potential methods of improving educational outcomes. Drawing on a comprehensive search of academic databases and relevant literature, key trends, including multiple framework designs, are presented and explored to review the role, relevance, and applicability of prompt engineering to purposefully improve GenAI-generated responses in higher education contexts. Multiple experiments using a variety of prompt engineering frameworks are compared, contrasted and discussed. Analysis reveals that well-designed prompts have the potential to transform interactions with GenAI in higher education teaching and learning. Further findings show it is important to develop and teach pragmatic skills in AI interaction, including meaningful prompt engineering, which is best managed through a well-designed framework for creating and evaluating GenAI applications that are aligned with pre-determined contextual educational goals. The paper outlines some of the key concepts and frameworks that educators should be aware of when incorporating GenAI and prompt engineering into their teaching practices, and when teaching students the necessary skills for successful GenAI interaction.

Keywords: Prompt engineering, Higher education, Generative artificial intelligence, ChatGPT

Introduction/background

Artificial Intelligence (AI) is now prevalent in many facets of modern societies and has recently taken a major step toward greater public awareness, acceptance and engagement with the releases of the latest generations of Generative Artificial Intelligence (GenAI) applications that can produce human-like textual responses and digital art (Bozkurt, 2023; Jacobsen & Weber, 2023; Spasić & Janković, 2023). The ease of use and public accessibility of these tools has had dramatic repercussions across many industries, including education. Within recent literature, there has been a diverse range of reactions within Higher Education (HE) to GenAI, particularly in relation to issues regarding academic integrity (Barrett & Pack, 2023; Kumar et al., 2024; Moya et al., 2023) and curriculum integration (Memarian & Doleck, 2024; Thurzo et al., 2023; Zawacki-Richter et al., 2024). Successful use of GenAI requires logical and insightful design of the prompts submitted into the AI systems. In HE, students are likely to use AI, therefore the skills of prompt engineering are becoming increasingly important for students, and for graduates as they enter industry (Raftery, 2023).

Prompt engineering is the "steering mechanism" (Cain, 2023, p. 5) by which users of GenAI craft their prompts to generate more desirable outcomes. The measure of desirability may be accuracy, relevance, applicability, or some other metric important to the user. Prompt engineering is a skill that can be learned and developed. Therefore, it can also be taught, and the surrounding pedagogy researched. In February 2022, before the release of OpenAI's ChatGPT3.5, arguably the most influential GenAI tool (Aydin & Karaarslan, 2023; Hu, 2023), Hocky and White (2022) stated: "prompt engineering, literally learning to interface more clearly with an AI, is now a research topic" (p. 80). In November 2023, Zheng and Fischer (2023) observed there is still a knowledge gap: "there exists a gap in knowledge pertaining to prompt engineering and its performance, specially in comparison to existing methods" (p. 2).

In an era where AI integration in HE is rapidly evolving, well-developed understanding of prompt engineering skills could improve student performance (Heston & Kuhn, 2023) and improve critical thinking skills (Walter, 2024). For example, Arizona State University offers a short online course through their CareerCatalyst program that provides students with prompt engineering skills (Arizona State University, 2024). The University of Sydney offers resources and practical examples of prompt engineering specifically designed to help students utilize generative AI tools like ChatGPT to enhance their learning (Liu, 2023). These examples illustrate that prompt engineering is not just a theoretical concept but has begun to be actively taught and applied in educational settings.

While reviewing the literature for this study no discussion on methods for assessing student's skill levels in prompt engineering were found. Also, no papers compared or contrasted the multiple ways in which prompt engineering is being taught in Higher Education. This paper addresses the latter gap. This study examines, via a systematic literature review, how HE has been engaging with prompt engineering to find foundational concepts and frameworks for use in curriculum and policy design. It synthesizes existing discourse that focusses on prompt engineering and its applications in HE curricula, and covers applications of prompt engineering, compares frameworks, and discusses the importance, relevance and methods of teaching practical skills in meaningful prompt engineering. The research addresses the question: How can prompt engineering be effectively included in Higher Education curricula?

Methodology

The research was conducted using the protocols of a systematic literature review, as outlined by Kitchenham and Charters (2007), Xiao and Watson (2019), and Tawfik et al. (2019), to determine the current state of discourse surrounding the topic of prompt engineering in HE. The search terms "Prompt Engineering", "Higher Education", "University" and "Curriculum" were entered into four search engines with the inclusion criteria of: peer-reviewed articles published since 2022 and published in English. The limited publication date criterium was selected to maintain relevance considering the impact

Table 1 Search process and results

Search engine	Search terms	# of results
EBSCOhost*	"Prompt Engineering""Higher Education"	6
EBSCOhost*	"Prompt Engineering" University	25
EBSCOhost*	"Prompt Engineering" Curriculum	1
ProQuest	"Prompt Engineering""Higher Education"	134
ProQuest	"Prompt Engineering" University	601
ProQuest	"Prompt Engineering" Curriculum	101
JSTOR	"Prompt Engineering""Higher Education"	1
JSTOR	"Prompt Engineering" University	1
JSTOR	"Prompt Engineering" Curriculum	5
Eric	"Prompt Engineering" Higher Education	2
Eric	"Prompt Engineering" University	2
Eric	"Prompt Engineering" Curriculum	1

* EBSCOhost Education Research Complete

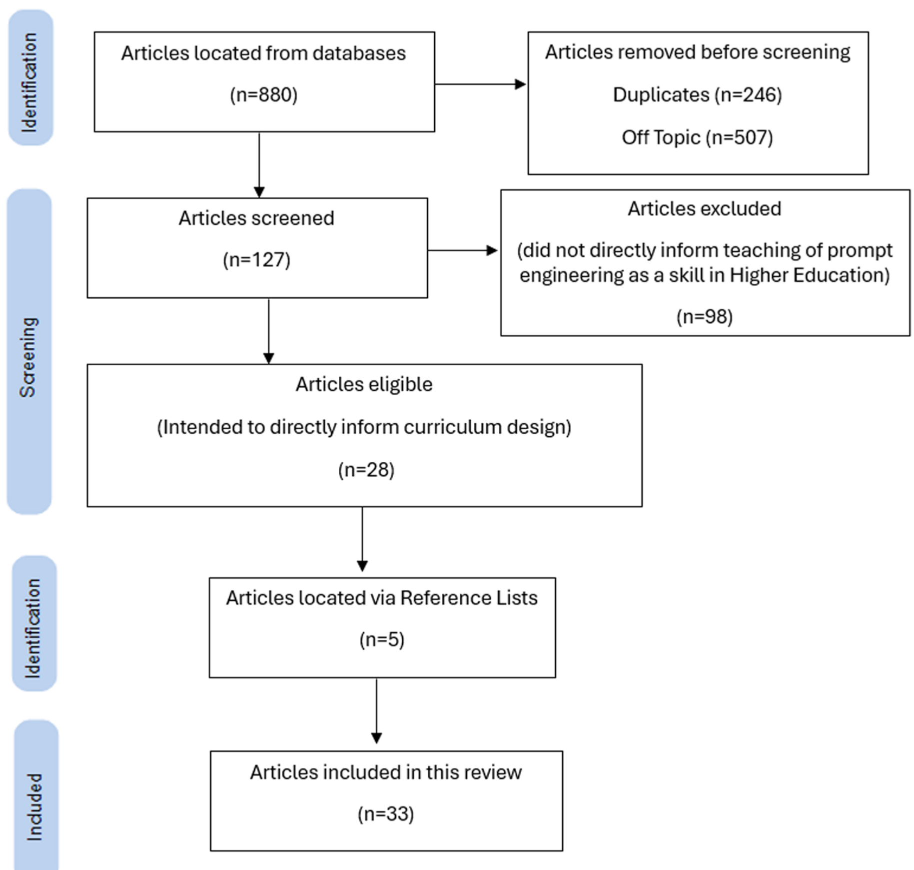

Fig. 1 Search and screening process

ChatGPT, and similar Large Language Models (LLMs), have had on HE has made previous research on this topic almost redundant. Table 1 and Fig. 1 show the results of the initial search process.

Including duplicates, a total of 880 potential articles were located. After removing duplicates, these were initially deductively assessed to ensure they included content on Artificial Intelligence, Higher Education and prompt engineering in ways that could meaningfully inform curricula. Assessment of inclusion was conducted by reading the articles' titles, abstracts and conclusions as a first pass. The second screening pass employed the following inclusion criteria:

1. The article must directly discuss the teaching of prompt engineering, and
2. The research setting must be Higher Education.

Articles that were excluded included off-topic phrases like "this would prompt engineering changes" or "a way to prompt engineering students to think", or were set in non-tertiary education environments, and were therefore not relevant to this study. Twenty-eight articles were selected for inclusion. An ancestral search of these articles revealed a further five relevant articles, totalling 33 articles in this review. The included articles were reviewed by both authors independently for salient themes. Once themes were agreed upon, the authors classified each paper against them independently. Where there was disagreement, the authors met and discussed the issues and came to a final decision.

Findings

Nature of papers

The majority of papers (n = 18) were disseminations of experimental research exploring prompt engineering. Twelve were case studies covering a range of applications of prompt engineering in HE settings including informed decision making (Abdulshahed, 2023;), graduate job classification (Clavié et al., 2023), assessment design (Eager & Brunton, 2023), curriculum design (Fotaris et al., 2023; Spasić & Janković, 2023; Tupper et al., 2023), creative workflows (Hutson & Roberston, 2023; Vartiainen & Tedre, 2023; Vartiainen et al., 2023), learning analytics (Susnjak, 2023), information retrieval (Wang et al., 2021) and a hermeneutic approach to optimising prompt engineering (Henrickson & Meroño-Peñuela, 2023). Nine of the studies involved human participants in surveys, observations, and discussion groups, totalling 224 participants. The smallest study (Jacobsen & Weber, 2023) involved three participants, and the largest study (Raftery, 2023) involved 84. One study (Susnjak, 2023) sourced pre-existing data regarding 7108 students from a HE Institution's student management system.

The experimental papers all engaged with similar methodologies, exemplified by Schäffer and Lieder (2023):

> *The research behind this article focused in the beginning on writing different prompts to try out the wording and adjusting it by observing the output. Then, the results get evaluated, whether they express the intended task of generating an interpretation of a given text and documented. These steps of exploring, evaluating, and documenting are repeated several times until the model generates a viable interpretation. (p. 115)*

There were varying modes of evaluating the "viable interpretation" among the different experimenters. However, they were mostly subjective, and no universal metric of success emerged from the research. Metrics of success include alignment with users' intended goals (Eager & Brunton, 2023), "coherence and depth" of the responses (Cain, 2023, p. 4), and "Template Stickiness" (Clavié et al., 2023). Template stickiness refers to the percentage of outputs that fit a pre-determined output format and contains the labels as defined in the prompt. Henrickson and Meroño-Peñuela's (2023) primary goal was hermeneuticity. However, they admit hermeneuticity was subjectively determined by the reader (p. 5). Jacobsen and Weber (2023) created a coding system for quantitative analysis of the quality of the AI responses by adapting a pre-existing coding scheme for measuring the quality of teacher feedback. However, they felt the need to add an error category to take into account ChatGPT's tendency to hallucinate.

Among the experimental studies, Ali et al. (2023) designed and prototyped a GenAI chatbot application, while Hutson and Cotroneo (2023) employed a mixed-methods approach using student surveys, instructor feedback, and AI generated artifacts in a private Missouri liberal arts institution's digital art course to explore AI creation of poetry. A theory-driven coding manual for ensuring quality when integrating prompt engineering into AI generated student feedback based on learning analytics was developed by Jacobsen and Weber (2023). ChatGPT was found to be able to provide code, explain basic concepts, and create knowledge related to Statistical Process Control (SPC) practice, learning, and research (Megahed et al., 2023). It was also found to be able to answer online quizzes by Raftery (2023) who claimed learning to write good prompts helps students understand all the steps to solve problems. Schäffer and Lieder (2023) combined a case study with an explorative evaluation in which they used prompt engineering to train a Natural Language Processer (NLP) to create machine-generated interpretation of texts. Knoth et al.'s (2024) mixed-methods study investigated how university students engaged in prompt engineering when interacting with ChatGPT3.5-Turbo by completing tasks designed to replicate two different use scenarios, one for leisure and one in a HE setting. Overall, there exists a broad range of experimental approaches, with results measured subjectively and currently with small data sets. However, within the papers there also exists a series of key themes emerging. Inductive analysis of the 33 papers in this review found they addressed five key themes identified from the data: Skills, Shots, Administration, Creativity, and Frameworks. Table 2 shows the frequency of each theme among the 33 papers. The most prominent theme is the concept of prompt engineering as a learnable, and therefore teachable, skill. This supports the premise of the paper. The

Table 2 Frequency of themes

Theme	Number of papers addressing the theme
Skills	22
Administration	18
Creativity	17
Frameworks	17
Shots	9

least prominent theme is no less important; Walter (2024) describes "various prompt types, such as the difference between zero-shot and few-shot prompting" as the "cornerstone of implementing prompt engineering" (p. 24).

Skills

Twenty-two publications directly address the concept of teaching the skill of prompt engineering to HE students. Eager and Brunton (2023) state: "the ability to write prompts is anticipated to emerge as a crucial competency for harnessing the potential of AI in augmenting teaching and learning practices" (p. 2). In Heston and Kuhn's (2023) discussion on prompt engineering in medical education they observe a chatbot can investigate a topic notably faster and potentially more thoroughly than a student can using search engines, online reference databases, or textbooks. They claim a deep understanding of prompt engineering could increase the quality of the output and conclude skills development can potentially improve student performance in areas such as patient interviewing.

Hutson and Cotroneo's (2023) experiments in AI art and design education resulted in useful information regarding prompt engineering to achieve desired outcomes. For example, they found: "Placing formatting considerations, like "photorealistic", at the end of the prompt resulted in more "photorealistic" outcomes than starting the prompt with such wording" (p. 8, parenthesis theirs). Findings from Wang et al.'s (2021) experiments engaging with ChatGPT in flipped classrooms, support the effectiveness of OpenAI's advice for writing prompts.

A primary role of HE is to prepare students for industry. Prompt engineering is a "skillset" Mabrito, 2024, p. 129) that has been identified as necessary for success in the future workplaces (Hazari, 2024; Henrickson & Meroño-Peñuela, 2023; Lacey & Smith, 2023; Raftery, 2023). Abdulshahed described the skill as "becoming increasingly important" (2023, p.1), and Cain described it as an "emergent critical skill set" (2023, p. 1). Spasić and Janković (2023) stated it had already become an "increasingly valuable skill" (p. 47). Prompt engineering skills include aptitude with language and writing, composing functionally valuable prompts, critical analysis of the outputs, problem solving, and adaption of follow-up responses (Hazari, 2024; Lacey & Smith, 2023; Mabrito, 2024). Wang et al. (2021) describe skilful prompt engineering as an "art" (p. 5) and liken it to "scientific inquiry skills" (p. 6). Training and practice are required to master prompt engineering skills (Korzynski, 2023).

Administration

This theme was the second most discussed among the discourse reviewed, appearing in 18 papers. AI technologies provide flexible and trainable tools that can be used to make better informed choices specific to unique requirements and conditions to each institution. This is exemplified by Abdulshahed's (2023) study in which decision makers within Lybian universities incorporated prompt engineering into Grey Theory to evaluate online conferencing and video sharing applications. Grey Theory is a methodological means to analyse uncertain systems containing incomplete information or small sample sizes and a grey system is one containing knowns and unknowns (Deng, 1982, p. 288). Abdlushahed found by combining Grey Theory with prompt engineering techniques enhances decision makers' abilities to make informed choices which consider case specific needs and conditions. Susnjak's (2023) study demonstrated a model for identifying learners at risk of programme non-completion which used ChatGPT for data extraction and to generate personalized meaningful feedback in natural language.

The prompt engineering skills used by HE staff in AI assisted administration tasks were identified as learnable, and therefore teachable, and could be incorporated into relevant curricula. Cain (2023) states: "Administrators and policymakers could support prompt engineering by providing resources for training and implementation, integrating LLM AI into educational programs" (p. 7). Some more specialised applications include using ChatGPT to assist with designing educational escape rooms (Fotaris et al., 2023), enhancing personalised learning (Cain, 2023; Heston & Kuhn, 2023; Hutson & Roberston, 2023) and to supplement traditional teaching of methodological competence through research workshops (Schäffer & Lieder, 2023). Some experiments exploring prompt engineering were specific and the outcomes may be less transferable. For example, Zheng et al. (2023) used prompt engineering to guide ChatGPT in the automation of text mining of metal – organic framework synthesis conditions from diverse formats and styles of scientific literature.

Generative AI can be used to assist in lesson design. A standardised prompt can be supplemented with additional definitional guidance, and seed words, in the process of preparing teaching units and lessons (Spasić & Janković, 2023). Spasić and Janković (2023) experimented with incremental development of prompts to generate a lesson plan for teaching a sequence of instructions. They found that "carefully tailored standard prompting" (p. 50) can be supplemented with role and word definitions for greater contextual specificity and claim this could become teachers' "strategy of choice" during the lesson plan generation process. In designing field trips, ChatGPT can be "piloted to excellent results" (Tupper et al., 2023, p. 10). However, human attribution is still necessary to achieve the best results, as without experienced prompt engineers who understand all the variables that dictate success, ChatGPT may deliver suboptimal output. Tupper et al. (2023) designed a workflow for effective prompt engineering to design field trips. They found it was highly efficient and claim it can reduce time and effort in field trip design and can be used "for any field course design and can competently complete most of the tasks involved, from choosing learning objectives and activities through to assessment and evaluation" (p. 10).

Well prompted GenAI is also a useful tool in assessment design. Testing AI's ability to meet learning outcomes via sequentially developed prompts can be used as a strategy for assessment redesign and it can also be useful for understanding how to integrate GenAI into the assessment process in an ethical and constructive manner (Raftery, 2023). Eager and Brunton (2023) ran workshops that experimented with prompt engineering processes to explore assessment redesign in response to concerns regarding AI in HE. Their process began with training ChatGPT on the unit curriculum and existing assessment design. This was followed by adding additional context to support divergent thinking in relation to authentic assessment. Their final stage involved "facilitating convergent thinking to guide ChatGPT to assist in the selection and authoring of assessment tasks" (p. 10). They observed academics were initially reluctant to engage, however as they worked through the process and developed higher order prompt engineering skills and understanding, they “started to appreciate the productive affordances of the technology and sought additional opportunities to use it” (p. 14).

Creativity

Generative AI holds great promise for transforming art and design and, therefore, the education of creative skills. Creativity was discussed by 17 papers from the review. AI can offer innovative ways to enhance creativity and idea generation as well as act as a virtual co-collaborator. It can also encourage collaborative activities between students (Hutson & Cotroneo, 2023). Developing skills in prompt engineering improves students’ abilities to transform AI from a “mere repository of information into an interactive tool that stimulates deeper learning and understanding” (Walter, 2024, p. 14). The difficulty of creating precise prompts that are capable of accurately assisting an AI agent to correctly represent complex issues in art, and nuances in formal analysis and artistic expression, illuminates the current limitations in AI technologies (Hutson, 2024). However, this limitation could be a valuable tool in teaching art critique.

A well-developed curriculum that teaches students how to integrate GenAI into creative processes may be able to improve their understanding of the role AI can play in creative processes, as well as how various prompt inputs influence the quality and novelty of the outputs. Mabrito (2024) states a scaffolded approach is crucial and argues for gradually progressing towards LLMs. It is important to incorporate thorough prompt engineering and hands-on experiences with AI tools in an active learning curriculum (Hutson & Roberston, 2023). This must include recognizing that while AI can be a valuable tool, it should not be viewed as a replacement for artistic processes, but rather as a mode of enhancing and complimenting the creative process. Educators must also address ethical and intellectual property issues related to the use of GenAI (Cain, 2023; Escalante et al., 2023; Hutson & Cotroneo, 2023; Tlili et al., 2023).

A common approach in arts education is teaching students to mimic previous influential figures. Teachers employing AI in fashion design lessons recognized some similarities between the way AI and humans build upon what they have previously encountered. Human design ideas are rarely completely unique, but reflect artists’, or students’, experience (Vartiainen & Tedre, 2023). Hutson and Schnellmann (2023) explored AI’s ability to mimic human emotion through poetry and claimed ChatGPT demonstrated an “impressive ability” (p. 11) to mimic the writing styles and word choices of poets. However, they insist the question remains as to whether true art can be generated by machines. They advocate for approaching human-AI collaboration with “healthy skepticism” (p. 3) as AI systems are designed to make informed decisions relying on data. So whilst advanced prompt engineering can simulate embodied interactions that are crucial for human learning and development including somatosensory, motor, and visual development through the process of virtual craft making, there are suggested caveats to its use.

Frameworks

Nine papers offered strategic prompt engineering frameworks to assist with engaging with AI for optimum benefit, and a further eight papers discussed the frameworks. Tupper et al.’s (2023) “best practice workflow” asks four questions: What, When, Where and

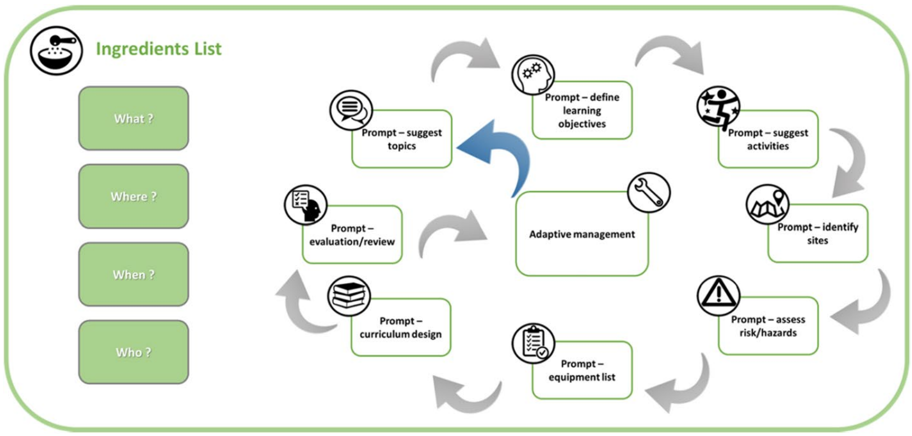

Fig. 2 Tupper et al.'s "Best Practice Workflow" (2023, p. 9)

Table 3 White et al.'s (2023) six categories of prompt patterns

Pattern Category	Prompt Pattern
Input Semantics	*Meta Language Creation*
Output Customization	*Output Automater* *Persona* *Visualization Generator* *Recipe* *Template*
Error Identification	*Fact Check List* *Reflection*
Prompt Improvement	*Question Refinement* *Alternative Approaches* *Cognitive Verifier* *Refusal Breaker*
Interaction	*Flipped Interaction* *Game Play* *Infinite Generation*
Context Control	*Context Manager*

Who (p. 9). It is specifically designed to develop field trips and is not directly transferable to other contexts. However, this specificity may be its strength and could be used as a model for developing other context-specific workflows. The elements they list which make this an effective workflow are: "emphasising clear objectives, sequential prompting, and feedback loops" (p. 1). Figure 2 shows the Tupper et al. workflow map, demonstrating the sequences and feedback.

White et al. (2023) claim "[p]rompt patterns are essential to effective prompt engineering" (p. 1) and they offer "reusable solutions to specific problems" (p. 2). In their article they compare prompt patterns to software patterns and present a framework for documenting and applying a catalogue of prompt patterns. They present six categories of prompt patterns, and 16 example patterns, depicted in Table 3:

The first category, *Input Semantics*, considers how a Large Language Model (LLM) understands the prompt and translates it into something it can use to generate output. *Output Customization* focuses on constraining and/or tailoring the properties of the output generated by the AI agent. *Error Identification* identifies and resolves errors in the AI generated output and allows for *Prompt Improvement* to increase the quality of both the input and output. It is within this category that the majority of the previously reported experiments fit. The *Interaction* category is concerned with the interaction between the human operator and the AI agent, and *Context Control* focuses on bounds and scope of the contextual information offered to the AI agent in training. A good example of this is the Tupper et al. (2023) experiment designing a field trip.

In an explorative development of a GenAI tool to act as a mentor to assist with self-guided learning, Ali et al. (2023) tested ChatGPT's ability to meet three quality indicators:

1) Goal fidelity: How well the interactions aligned with the goal of each learning approach.
2) Cognitive guidance: Help or assistance initiated by chatbot.
3) Social-emotional support: How responses related to emotion and motivation such as positive affirmation, showing empathy, promoting self-efficacy/confidence, and other related constructs.

They found that by assigning the chatbot explicit roles, using active voice with verb sentences and stacking synonyms, these prompt engineering strategies "strongly increased alignment of chatbot responses to the three indicators" (p. 139). They provide examples of their engineering prompts. The following example demonstrates their training strategy:

> *You are a teacher who facilitates deep construction of knowledge. This involves any one of the following: building on prior knowledge, selecting information, organizing information, integrating ideas, making inferences, and formulating new concepts. When I ask questions, guide me in the form of hints, clues, or suggestions one step at a time. Try not to give me a direct answer. (p. 142)*

This example shows the personification technique which was prevalent among the literature and found to be a common successful strategy (Fotaris et al., 2023; White et al., 2023). Alternative formats of personification include designating a style (Wang et al., 2021) or dictating a setting exemplified by the following prompt from Heston and Kuhn (2023): "You're at a fork in the road in which one direction leads to the City of Lies (where everyone always lies) and the other to the City of Truth (where everyone always tells the truth)" (p. 1, parenthesis theirs), and Korzynski et al.'s (2023) example: "You are a salesperson in a technology company…" (p. 30). More specific examples include Hutson and Schnellmann's (2023) designation of an individual poet's style when they asked the AI to "personify and use the voice of the English Romantic poet John Keats (1795–1891) when generating a poem about Autumn" (p. 3). Employing the personification concept can also elicit greater user interaction. Tlili et al. (2023), observed participants felt their chatbot became their "personal assistant" (p. 9) inducing emotional responses in the user including gratitude. Ali et al. (2023) claim generative AI can act as an "on-demand and personalized external other" (p. 136) and categorise multistage prompts, engineered to represent a single accepted view, as "persona prompts" (p. 139).

Abdulshahed (2023) combined the "cutting-edge methodology" (p. 1) of prompt engineering with Grey Theory (Deng, 1982) to develop their framework for a systematic decision-making technique designed specifically for the distinct requirements of Libyan universities. The framework designed and tested in this paradigm would be adaptable and applicable to a wide range of situations to incorporate a holistic approach into the decision-making process. One paper discussed the relationship between an existing framework for specific educational design and ChatGPT (Fotaris et al., 2023) and one paper proposed a framework (Susnjak, 2023) that unifies both transparent machine-learning as well as techniques for enabling prescriptive analytics.

Three articles presented acronym frameworks; AIPROMT, CLEAR and CRISPE, for reliable and relevant applications of prompt engineering (Korzynski et al., 2023; Lo, 2023; Wang et al., 2021). Korzynski et al.'s (2023) AI PROMPT framework is designed to provide clear and actionable suggestions for text-to-text prompt engineering. This is intended to help users of AI LLMs refine their prompts to produce better quality responses from AI applications. Table 4 shows the AIPROMPT acronym's meaning and intentions.

A similar acronym-based framework, developed by Lo (2023) is also intended to elicit more effective AI generated content. The author claims students can use this framework to navigate AI content and nurture critical thinking skills necessary for interactions with AI. Table 5 shows Lo's CLEAR framework.

Lo implores readers to consider how the CLEAR framework can be incorporated into information literacy instruction and suggests by employing the approach students will develop into critical thinkers in the AI era.

Wang et al. (2021) used a comprehensive analysis to explore the effectiveness of the CRISPE framework, developed and offered by OpenAI, in improving the quality of outputs obtained from ChatGPT. CRISPE stands for the following:

Table 4 AIPROMT acronym (Korzynski et al., 2023, p. 31)

Acronym	Recommendation	Description
A	Articulate the Instruction	Clearly state the task to be performed, such as 'write', 'classify', 'summarize', or 'translate', and specify how the output should look (table, list, Python code).
I	Indicate the Prompt Elements	Show the model where the instructions and input data are and what the expected output format should be.
P	Provide ending cues and context	Offer the model clear ending cues, such as three dots for continuation or a colon, dot, or placeholder like 'answer' for indication a response is needed. Furthermore, ground the model by providing a context for the task (*e.g.* 'you are a manager of a tech team').
R	Refine instructions to avoid ambiguity	Give the model-specific instructions and a detailed description of the task to avoid and confusion or impression.
O	Offer feedback and examples	For conversational models, such as ChatGPT, feedback on the model's responses can help it better understand the desired output. Moreover, providing the model with a few examples of expected responses (few-shot learning) can help it adapt its style and way of responding.
M	Manage interaction	Treat the model as your sparring partner, asking it to provide counterarguments or point out flaws in your ideas.
T	Track token length and task complexity	Break complex tasks into smaller steps for better performance. Remember to control the token length, keeping the prompt and response under the token limits of the model (usually 4096 tokens for commercially available LLMs). The token length of a text can be checked here: https//platform.openai.com/tokenizer

Table 5 CLEAR framework (Lo, 2023, p. 2)

Acronym	Recommendation	Description
C	Concise: brevity and clarity in prompts	A concise prompt removes superfluous information, allowing AI language models to focus on the most important aspects of the task, resulting in more pertinent and precise responses. Clarity is also crucial, as unclear or imprecise instructions may result in AI-generated content that does not meet the user's needs or expectations.
L	Logical: structured and coherent prompts	A logically structured prompt comprises information which follows a natural progression and the relationships between concepts are evident. It enables AI models to better comprehend the context and relationships between various concepts, resulting in more accurate and coherent outputs.
E	Explicit: clear output specifications	Explicit prompts include specifics about the type of information required, how it should be conveyed, and precise instructions regarding the desired output format, content, or scope, thereby reducing the likelihood of receiving unanticipated or irrelevant responses from the AI model.
A	Adaptive: flexibility and customization in prompts	Adaptability entails experimenting with various prompt formulations, phrasings, and settings in order to establish a balance between creativity and concentration thereby adapting the AI model's responses to the specific requirements of each task.
R	Reflective: continuous evaluation and improvement of prompts	Adopting a reflective perspective is vital for staying ahead of the curve and adapting to the ever-changing field of AI as it enables users to evaluate the performance of their AI model based on user feedback and their own assessments, identifying areas for improvement and adjusting their approach accordingly.

CR: *Capacity and Role.* What role do you want ChatGPT to play?

I: *Insight.* What background information and context do you want ChatGPT to provide?

S: *Statement.* What do you want ChatGPT to do?

P*: Personality.* In what style or manner do you want ChatGPT to answer you?

E: *Experiment.* Ask ChatGPT to provide multiple answers for you (Wang et al., 2021, p. 7).

They found prompts generated by following this framework can elicit more complete and in-depth answers when compared to free-style unstructured prompts (Wang et al., 2021). However, in order to maximize the positive impact of engaging with LLMs in education settings, students should not only learn how to master prompt engineering techniques, but they must also, prior to beginning the activity, already possess some prerequisite knowledge relevant to the task. Without this prior knowledge, the students will not be capable of reliably assessing the AI agent's outputs for meaningful development.

Critical thinking approaches are common within the literature. Heston and Kuhn (2023) note if a student prompts an AI agent to write an essay it "robs the student of the opportunity to think critically" (p. 203). However, prompt engineering can be used in education to encourage and apply critical thinking and analysis (Ali et al., 2023; Bozkurt & Sharma, 2023; Eager & Brunton, 2023; Fotaris et al., 2023; Hutson & Cotroneo, 2023; Tupper et al., 2023; Wang et al., 2021). Employing prompts that are designed to encourage exploration of the subject matter, develop stimulating questions, or conceive pragmatic solutions can encourage active engagement and promote higher-order thinking abilities among students (Eager & Brunton, 2023). Cain (2023) lists three "pivotal components" (p. 4) that underpin effective prompt engineering: Content Knowledge, Critical Thinking, and Iterative Design. He claims critical thinking "isn't a mere accessory but a necessity" (p. 4) and explains its role in evaluating, verifying, and questioning the AI tool's outputs. This is essential for detecting hallucinations, biases, inaccuracies, or any other forms of unsuitable content in the AI's responses. Such skills are fundamental to then being able to adjust prompts accordingly. Figure 3 shows Cain's prompt engineering framework featuring his three pivotal components.

Fotaris et al.'s (2023) study specifically examined the interaction of ChatGPT with Room2Educ8 – a pedagogical design framework for guiding educators and learning designers through the process of using escape rooms as educational experiences. A significant part of the prompt engineering is initially acquainting ChatGPT with the framework. The authors claim this initial step will ensure the AI tool will comprehend the framework, thus enabling it to generate relevant responses. In a detailed exposition of their process, the authors give examples for eight stages of curriculum development including 27 specific aims and 45 prompt examples. They precede their examples with the following disclaimer: "While it is essential to acknowledge that ChatGPT's responses are generated by AI and may not invariably align precisely with designers' expectations, they nonetheless represent a valuable source of inspiration and an effective starting point for the creative process" (p. 183). They acquaint the AI agent with the conceptual framework and designate a persona for the AI agent to embody. This personification is an important part of the process. Each instruction must be "initiated with a clear and precise directive" (p. 186) and maintain alignment with the learning objectives and educational goals. Finally, the active use of feedback loops is necessary to refine prompts for iterative improvements.

Susnjak (2023) developed and evaluated, via a case study, a Prescriptive Learning Analytics Framework (PLAF) for identifying learners at risk of non-completion. It demonstrates how transparent and responsible predictive modelling can be enhanced with prescriptive analytics to produce relevant human-readable feedback through advances in large language models to students at risk. He suggests three stages:

1. Provide the AI agent with a well-defined unambiguous prompt that outlines the purpose and scope of the feedback request.

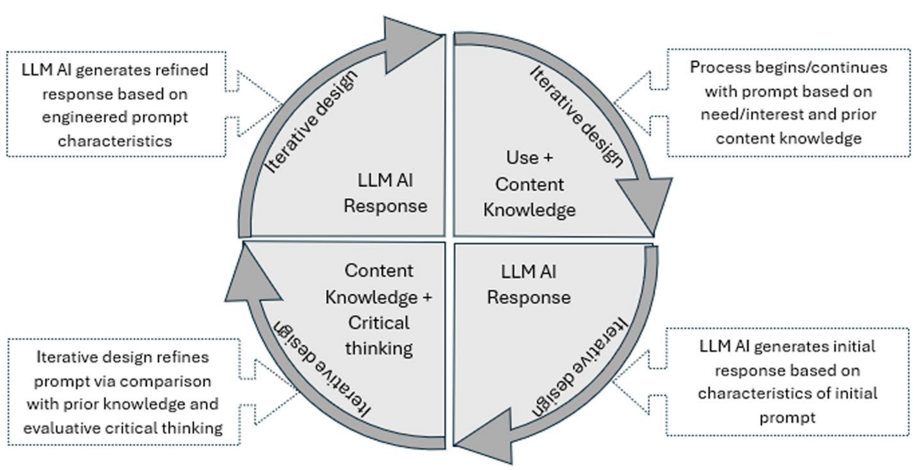

Fig. 3 Cain's (2023) prompt engineering framework

2. An example feedback template should be provided to serve as a reference and a primer for the output format that is expected from ChatGPT.
3. The actual data used to generate the prescriptive feedback must be provided. (p. 25–27)

He includes examples of prompts demonstrating training of the AI agent with example templates prior to requesting natural language feedback. In their case study exploring prompt engineering for job type classification, Clavié et al., (2023) provide examples of "loose" and "strict" templates. Figure 4 illustrates their provided examples:

Overall, there are three concepts the frameworks have in common which are summed up by Spasić and Janković (2023):

1. Be very specific in your instructions,
2. Ask GPT to break its work into small chunks, just as you would with a human, and
3. Ask GPT to check and improve its own output. (p. 47)

A more comprehensive amalgamation of the frameworks, yet with an objective of remaining pragmatically simple is:

1. Define role: Explain to the AI agent who it is (Ali, et al., 2023; Wang et al., 2021).
2. Provide background: Inform AI agent of context (Wang et al., 2021).
3. Define objectives: Explain to the AI agent your goals (Tupper et al., 2023).
4. Set parameters: Allow or limit tolerances (Abdulshahed, 2023).
5. Be precise: Ensure your instruction or question is concise and explicit (Lo, 2023).
6. Specify format: Describe or even provide a template (Clavié et al., 2023; Susnjak, 2023).
7. Rinse and repeat: Critically assess the response in relation to your requirements and adjust your prompt accordingly to elicit more useable responses (Cain, 2023; Korzynski et al., 2023; Lo, 2023; Wang et al., 2021).

It is also important the user understands the AI tool's capabilities and limitations, and the types of queries which elicit the best performance from each tool. This knowledge will help users engineer prompts that maximally align with the tool's performance. However, with specifically crafted prompts it is possible to "jailbreak the AI" (Bozkurt & Sharma, 2023, p. 3) and cause it to produce responses it is not designed to create. This process of jailbreaking can be achieved by assigning the AI agent specific

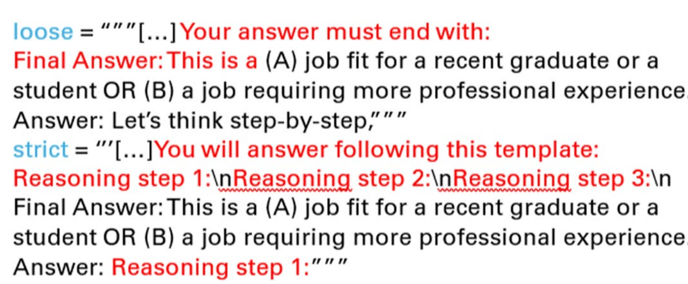

Fig. 4 Clavié et al.'s (2023) "Loose" and "Strict" template example

personifications or roles and in some cases can potentially elicit more informative or meaningful responses. A typical assessment design in the future may move from assessing the written product to assess the students' prompt engineering, thus testing they can investigate a topic insightfully using AI tools (Lacey & Smith, 2023).

A tactic only mentioned once in the literature that is a straightforward and appropriate method of generating relevant prompts is to ask the LLM to advise suitable prompt ideas or designs. In a discussion about prompt engineering as an important emerging skill, Meskó (2023) provides the following example: "What prompt could I use right now to get a better output from you in this thread/task?" (p. 5).

Walter (2024) created a tabulated summary of established prompt engineering methods from seven sources of literature. Table 6 presents an extract from Walter's summary:

Walter's table features a developing complexity of prompt engineering methods which could be very useful in scaffolded curriculum development. He highlights the role narrative plays in yielding improved results by assuming the persona of a person with a specific role. This helps the AI agent model produce greater specificity in its responses. Walter suggests to enhance AI literacy skills in academia, a "nuanced approach is essential" (p. 22). This involves integrating AI literacy into existing curricula, adopting an interdisciplinary approach, and catering to individual students' learning styles. Collaborative sessions between lecturers and students should comprise experimenting with different prompts to discover which are more effective, identifying which prompt engineering methods yield optimum results for different objectives.

Shots

An emerging terminology among the literature was the concept of "shots" which was discussed in nine papers (Clavié et al., 2023; Escalante et al., 2023; Henrickson & Meroño-Peñuela, 2023; Heston & Kuhn, 2023; Korzynski et al., 2023; Schäffer & Lieder, 2023; Walter, 2024; Wang et al., 2021; Zheng et al., 2023). A zero-shot prompt is one that does not include any detail or context, for example "Write a Haiku". Zero-shot prompting

Table 6 Summary of established prompt engineering methods (Walter, 2023, p. 15)

Prompting Methodology	Description
Input–Output Prompting	The classic form of prompting: simple input, simple output
Chain-of-Thought Prompting	The AI should slowly elaborate on how a given response is generated
Role-Play or Expert-Prompting	The AI should assume the role of a person or an expert before providing an answer
Self-Consistency Prompting	The AI should generate several responses and discern itself, which would be the best answer
Automatic Prompt Engineer	The AI model is provided with several examples, and it should help us to find an ideal prompt to arrive at these examples (we can then further work with the resulting prompt)
Generated Knowledge Prompting	Before prompting the AI with our actual task, we first let the model generate knowledge about the topic so that it already has set the right scene for its responses
Tree-of-Thought Prompting	The AI is provided with a complex setting where it is prompted to use its arguments like a chess game, providing several lines of thoughts and go back again if there are inconsistencies, eventually to converge on the best response.

enables an AI agent to make its own predictions without the need for any additional training (Korzynski et al., 2023). A one-shot-prompt contains a single piece of guiding context, such as "Write a Haiku about an albatross". More details, or "shots" typically increase the quality of AI responses (Schäffer & Lieder, 2023). Prompts containing more contextual information that pre-trains the model appears to have higher chances of producing meaningful output (Henrickson & Meroño-Peñuela, 2023). Zheng et al. (2023) found providing four or five short examples in a "few-shot" (p. 10852) strategy enabled more effective and streamlined responses.

Clavié et al. (2023) devised a sequential experiment beginning with a zero-shot "baseline" prompting, followed by "few-shot chain-of-thought prompting" (p. 10) comprising classification examples in the form of mock conversations involving elaboration on reasoning. Thus, they attempted to elicit reasoning by prompting the model to think sequentially. Their results indicate the impact of prompt engineering on their metrics of success is high. However, the authors did observe few-shot prompting with examples had the potential to perform noticeably worse and they speculated that this was due to the examples biasing the model. This contrasts with Henrickson and Meroño-Peñuela's (2023) exploration supplying "increasingly rich shots" (p. 9) to ChatGPT. They hypothesised that progressively giving ChatGPT more specific details they would observe increasing degrees of quality outputs. They found ChatGPT seemed to "more precisely, almost surgically" (p. 11) meet their needs with this strategy.

Discussion

Artificial intelligences, in the form of LLMs and other generative applications, have a significant presence in the twenty-first century. They have made rapid inroads into both industry and education, and have been purposed by educators and students for a large variety of tasks. In preparing students for industry, it is the duty of higher education to ensure students are capable of meaningfully and productively engaging with AI. Bozkurt and Sharma (2023) stress the importance of understanding how subtle nuances in language impacts generative AI's responses.

Prompt engineering is an evolving skillset that should be taught to students (Aaron et al., 2024; Zawacki-Richter, 2024). However, as it is "still in its infancy" (Ali et al., 2023, p. 139) it is unclear how LLMs respond to varying higher-order levels of prompts and individual task-oriented training. It has been demonstrated by the experiments in the literature that the quality of AI generated outputs can be highly influenced by the quality of the prompts: "prompt engineering requires preparation and testing for a successful output in the form of a viable interpretation" (Schäffer & Lieder, 2023, p. 115). The quality of prompts is, however, both subjective and contextual. Various frameworks have been developed, tested and presented by researchers across multiple contexts. However, it should also be noted Yeadon and Hardy (2024) argue as AI systems become more user-friendly and intuitive, the requirement for specific AI literacy skills decreases. They suggest specialized knowledge in AI literacy skills like prompt engineering may become unimportant, and admit the techniques discussed in their own research might be quickly outdated due to rapid developments in AI.

No single prompt engineering framework is ultimately transferable and there is no "clear path forward" (Eager & Brunton, 2023, p. 16). Some of the frameworks have been designed to meet specific purposes and some are more general. It is important that an appropriate framework is chosen when embarking on a task that uses prompt engineering. An effective curriculum for training and developing the skills for meaningful prompt engineering could involve students replicating the experiments conducted in the studies reviewed in this paper and reviewing these frameworks. Alternatively, the experiments and methodologies presented in these papers could be used as templates for in-class, take home, or assessment activities.

For example, a potential task for HE students may be to choose one of White et al.'s (2023) 16 patterns and run a trial within their chosen context or subject specialty. A cohort of students could compare and contrast a number of selected patterns. A curriculum for preservice teachers could include a task using Tupper et al.'s "Best Practice Workflow" to design a field trip. This could be adapted for field trips across a variety of subject areas. The students could then be tasked with re-purposing the workflow for something other than a field trip, assessing the results and adapting the model to create a new, context specific, workflow.

Interaction and feedback loops are common threads among the frameworks presented in the literature. This sequential and iterative process is ideal for a scaffolded approach to teaching and leads naturally to sequenced in-class activities and formative assessments. It is important that the students are involved in hands-on experimentation to ensure experiential active learning. This will progress naturally from low to higher order thinking skills as per Blooms' Taxonomy. However, as Eager and Brunton (2023) note, it is also very important that "the process of imparting AI literacies to students begins with the development of these literacies among educators. Therefore, professional development in this area is of paramount importance" (p. 16).

Critical approaches to AI are imperative. Developing skills in prompt engineering can be delivered as a critical thinking exercise (Walter, 2024). The processes of continuous evaluation and refining instructions, as presented in the prompt engineering frameworks found in the literature, are essential to developing valuable skills in AI interaction. Lo (2023) appeals to his readers to consider how his CLEAR framework can be integrated into curricula and claims this approach will develop critical thinking skills in students.

Two important concepts that seem to have a significant influence on the quality of outputs include personification and example templates. Personification includes telling the AI agent that it is, for example, a curriculum designer, or a teacher, or whatever role is contextually relevant. This is an integral part of process of training the AI agent and has the effect of creating more human-centred and immediately applicable products. Providing templates helps guide the AI agent to produce useable outputs that fit with pre-existing designs with minimal amendments. It also helps the AI agent to understand the requirements of the user. Experimenting with personifications and templates would be a valuable activity for students learning to engage with GenAI and would be easily assessable.

The themes identified in this study are not isolated. The creative skill level in crafting effective prompts, and critical thinking applied to shot development, directly influences the effectiveness of the prompts. Frameworks serve as structural guides providing a scaffold for educators to design curricula that promote meaningful discipline-specific learning and assessment. Concepts that engage across the themes include a need for educators to recognize a holistic approach that combines skill development with creative exploration. The five themes underscore the necessity of a comprehensive pedagogical strategy that prepares students to navigate the idiosyncrasies of AI in their respective disciplines. Educators should consider that a previously successful prompt will not be as useful or transferable a skill as being able to analyse and evaluate AI outputs and creatively respond with more purposefully engineered prompts. The understanding of the types of frameworks that support this are critical.

To effectively employ the various prompt engineering frameworks presented in this study across different academic disciplines, educators could tailor specific activities that align with the unique objectives of their fields. For example, when analysing a book in a literature course, educators could employ the CRISPE framework by asking students to define the role of the AI as a literary critic. Prompts could ask the AI agent to provide context about the text being analysed, and requesting a detailed character analysis. Critical analyses of the AI outputs could be an assessable task. In a STEM tutorial, tutors could guide students to employ the CLEAR framework to engage with AI agents acting as research assistants. Analyses of how accurately the outputs outline the background of a scientific concept or summarise recent findings could be an assessable task. In business studies, students could experiment with frameworks to create one that enables an AI agent to act as a market analyst. Students could provide data and ask for insights on market trends, responses to the AI outputs could be an assessable task. By integrating these frameworks into discipline-specific tasks, students would not only develop or enhance their prompt engineering skills, but also engage in meaningful, context-rich enquiry-based learning experiences that would simultaneously foster critical thinking and creativity across the curriculum.

The subjective nature of evaluating AI-generated outputs poses a significant limitation. The absence of standardized metrics for success means that assessments of prompt effectiveness, and therefore students' skill levels, can vary widely among educators and institutions. This variability can hinder the establishment of best practices and may result in inconsistent learning outcomes for students. Furthermore, the reliance on qualitative evaluations has the potential to be influenced by inherent biases that exist in AI outputs (Cain, 2023; Clavié et al., 2023). Another critical limitation considers how the rapid evolution of AI technologies can render existing frameworks quickly outdated. As new AI capabilities evolve, educators may find themselves needing to continuously adapt their teaching strategies, frameworks and assessment processes, or risk passively developing potential gaps in knowledge and skills. This dynamic landscape necessitates ongoing research as well as continuous professional and curriculum development driven by a commitment to staying current with technological advancements.

Assessment

Among the discourse on including prompt engineering in curriculum, there was little discussion regarding assessing students' prompt engineering skills. Hazari (2024) suggested a course format for AI literacy courses in HE with prompt engineering featuring prominently. However, there is no mention of how to assess these skills. Knoth et al.'s (2024) experimental study used two assessment tasks to explore AI literacy in university students. They created a quantitative prompt quality score based on prompt components proposed by Eager and Brunton (2023) including verb, focus, context, focus and condition, alignment, and constraints and limitations. They also conducted qualitative analyses using an inductive approach, as they observe there is "currently no comprehensive and validated prompt taxonomy" (p. 5). The prompts were coded according to specific features within the prompts: The number of words, the number of prompts used to solve the task, elements of human-like communication/communication style, and syntax type of sentence. In so doing they have set the groundwork for developing a valid prompt taxonomy. Furthermore, the assessment tasks provided by Knoth et al. in their appendices could be used as templates for prompt engineering assessment designs. We also note that assessment was only addressed in two papers and is requiring further attention.

This paper has addressed the research question: How can prompt engineering be effectively included in Higher Education curricula? From the content presented here, a curriculum could be developed that addresses each of the themes: Skills, Creativity, Administration, Shots, and Frameworks. Lesson time and student tasks could be developed that experiment with the application of the various frameworks, and use the frameworks presented here as templates to develop new context specific procedures. Any curriculum involving the teaching of skills related to using artificial intelligence would need to be flexible as the technologies are evolving rapidly. Prompt engineering skills, in conjunction with critical evaluation, will be a vital aspect of employability.

Conclusion

This paper presents a review of current literature on the topic of prompt engineering in the context of higher education. It presented various frameworks that have been developed by active and experimental research. There is much subjectivity regarding what is, or is not, a successful AI generated output and context is very important in this regard. As AI technology continues to develop, so will the necessary skillsets to meaningfully, and productively, engage with it in various contexts. Well-developed prompt engineering can simulate human interactions that are critical for learning and development of various skillsets. Training in high-order prompt engineering skills, including critical evaluation, is necessary to prepare students in higher education for industries engaging with AI technologies.

The literature reviewed in this article provide a variety of frameworks that could be of valuable use in developing prompt engineering curricula. This article will help curricula developers consider content in courses, or modules within courses, for developing prompt engineering skills. Educators could employ one or more of the presented frameworks where they naturally fit existing course content, or they could use the frameworks as templates to develop their own. Alternatively, they could use the frameworks as course content for students to explore, experiment and develop further. The largest gaps in the literature presently appear to be assessment methods for prompt engineering skills, and a comprehensive and validated prompt taxonomy. Future research could address these gaps, and longitudinal studies could present concepts of systematically validated prompts and examine the long-term efficacy of various frameworks.

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