

## PROMPT ENGINEERING IN HIGHER EDUCATION: A 21ST-CENTURY COMPETENCY FOR LIFELONG LEARNING IN LANGUAGE EDUCATION

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### Abstract

The rapid development of generative artificial intelligence has raised the question of how these technologies are being used by non-computing students to solve their day-to-day assignments in their academics. This study examined the influence of prompt engineering as 21st century skills for lifelong learning in English as a Second Language (ESL) context among undergraduate students of non-computing disciplines, considering the significance of use of Artificial Intelligence (AI) as integral part of learning. A survey was carried out on a purposive sample of 100 undergraduate students from four public and private sector universities in Sindh, Pakistan, excluding the students of Computing disciplines. Data was analyzed using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4. The results of the structural model study showed that prompt engineering has a significant and positive direct effect on the overall 21st-century skills, explaining 38.2% of the total variance. Item descriptive statistics indicated that students had the most utility in using AI to quickly find academic sources and the lowest utility in using AI to sustain reading attention on digital screens. Based on these findings, it is suggested that higher education institutions adopt formal, non-technical prompt engineering workshops in non-computing programs, to move students from intuitive to optimum AI use. In addition, teachers should adopt a balanced educational approach that combines AI-based text synthesis with offline active learning exercises to alleviate tiredness due to reading on the screen. Finally, the study shows that purposeful prompt engineering is a critical accelerator for greater digital and academic literacy.

### Introduction

Prompt engineering is an emerging field dedicated to the development and enhancement of prompts to efficiently leverage large language models (LLMs) in many applications and research domains. While it is universally possible to give a

general definition of 21st century talents because of the existence of many distinct frameworks, common elements of them can be identified. These are generic skills that are not exclusive to any single professional field and are vital for personal development in the ever-changing 21st

century (Foster & Piacentini, 2023). These skills include online information issue solving (Goldman & Brand-Gruwel, 2018) and other skills needed to analyze and process new information and properly apply it in a variety of settings (Foster, 2023).

Some research suggests that a large language model (LLM) can greatly increase its performance when stimulated in the right way, perhaps making specialized fine-tuning of a base model built on a general corpus unnecessary. For example, Nori et al. (2023) and Maharajan et al. (2024) showed that with proper prompting techniques, the effectiveness of LLMs can be improved to the extent that fundamental models outperform LLMs that are specifically fine-tuned in the medical domain. This demonstrates that prompting is a very powerful phenomenon with a huge impact on LLM performance.

Academic researchers and authors can harness the full potential of language models by using prompt engineering methodologies, and benefit from their benefits across a wide range of disciplines. This is useful in developing artificial intelligence systems and using them most efficiently in different applications such as text generation and image synthesis, problem solving, learning innovative ideas, brainstorming entrepreneurship ideas and solving day-to-day academic problems. However, the educational significance of developing technologies lies not only in their technical qualities, but also in their influence on cognitive engagement, metacognitive monitoring and self-directed inquiry of learners. Much research has demonstrated that children learn more when they are actively generating questions and checking their understanding and building their notions incrementally through inquiry-based engagement, rather than passively receiving information. A critical obstacle to the use of emerging artificial intelligence (AI) tools in education is understanding how students utilize them in relation to accepted definitions of active cognition and self-regulated learning. This study has

analyzed the issues and challenges faced by non-computing students while using AI for their classroom learning.

OpenAI's ChatGPT's launch of the generative AI (GenAI) in November 2022 has revolutionized the field of educational practices (Lo, 2023). ChatGPT demonstrates the promise of large language models (LLMs) to support personalized, interactive learning, where students can explore topics, pose questions, and engage in self-directed learning. Educators suggest using LLMs as a resource to boost teaching in a number of subjects, such as business (Alshater, 2022), engineering (Qadir, 2023) and nursing education (O'Connor, 2022) because of their ability to do a variety of tasks. Large Language Models (LLMs) are said to be able to support adaptive learning, automate essay evaluation, and deliver customized education, among other uses (Baidoo-Anu & Ansah, 2023). Theoretical frameworks for using LLMs in education have been developed, and research has investigated teaching students prompt engineering (PE) techniques, the process of formulating inputs to direct a GenAI system to produce more effective or precise outputs (Cain, 2024; Su & Yang, 2023).

### Hypothesis

- H1. The communication skills of students are significantly influenced by prompt engineering.
- H2. Prompt engineering significantly influences pupils' problem-solving capabilities.
- H3. The impact of prompt engineering on kids' creativity is significant.
- H4. Students' cooperation on scholarly endeavors is significantly affected by prompt engineering.
- H5: Prompt engineering plays a vital role in enhancing pupils' abilities to look for and retrieve knowledge.
- H6: Prompt engineering significantly influences comprehension during screen reading.

## Literature Review

### LLM for Learning in Higher Education

Despite the mixture of excitement and skepticism about the use of LLMs in improving student learning, several students have already used LLMs for educational purposes in both appropriate and inappropriate ways. Research shows that students have limited understanding of LLMs, often taking information on the surface without being able to make informed judgements or know how to ask relevant questions to LLMs to improve their learning (Ding et al., 2023). Teaching students how to use LLMs well for their learning is a complicated task that goes beyond teaching PE skills alone. The main purpose of physical education is to generate the necessary replies from the generative AI. Learning, however, usually involves students working with the generative AI to get a comprehensive understanding of a particular subject and not just looking for answers. Furthermore, due to the well-known hallucination problem related to LLMs, it is crucial to educate students to acquire a critical mindset to make well-informed evaluations of information or goods created by GenAI (Ferrara, 2024). I think it's crucial to understand how students use these technologies to further their learning before we can design effective laws to ensure proper and relevant engagement with LLMs.

Large language models (LLMs) are powerful tools for many natural language processing tasks given the correct stimuli. However, the optimal prompt is hard due to the sensitivity of the model (Reynolds and McDonell, 2021) and sometimes requires extensive manual trial-and-error efforts. Moreover, when the original prompt is put into production, unforeseen edge cases may appear, requiring more manual labor to iterate further on the inquiry. These issues have led to the emergence of a new research domain focused on autonomous prompt engineering. A major method in this area is to employ the powers of LLMs (Zhou et al., 2024). This means meta-prompting LLMs, for example: “analyze the

current prompt and a list of examples, provide feedback, and then propose a new prompt” (p.412). LLMs are good at producing text because they can produce content that is coherent and relevant to the situation from some prompt or input. These are essential tools for content creation, creative composition and automated narrative construction. In addition, LLMs are good at answering conversational questions, i.e. they can understand and respond to questions like an informed conversation partner.

In addition, LLMs are crucial in language translation processes. Their knowledge of the subtleties of multiple languages guarantees accurate and successful translations in a broad range of language combinations. Thanks to LLMs' capabilities, researchers and academic authors have accomplished significant progress in machine translation, which allows for better cross-cultural communication and understanding. Fast engineering methods can be applied to optimize LLMs like ChatGPT for better academic writing and for exploring new research and information dissemination paths.

When properly prompted, large language models (LLMs) are powerful tools for many natural language processing tasks. However, the sensitivity of the model (Jiang et al., 2020; Reynolds and McDonell, 2021;) makes it challenging to find the optimal prompt, often needing significant manual trial and error. Furthermore, once an initial prompt is put into production, it may encounter unforeseen edge cases, requiring subsequent rounds of manual intervention to improve the prompt. Such problems have inspired a new area of research called autonomous prompt engineering. One important way in this direction is to utilize the capability of LLMs themselves (Zhou et al., 2023; Pryzant et al., 2023). This requires meta-prompting LLMs with commands such as “critique the current prompt and a set of examples, give feedback, and then propose a new prompt.” Figure 1 These methods indicate impressive efficacy, although a relevant question

is: What makes a good meta-prompt for autonomous prompt engineering? To respond to this question, we connect two essential observations: At its heart, prompt engineering is a natural language generation problem that requires sophisticated thinking. It involves careful examination of the model's errors, developing hypotheses about the deficiencies or ambiguities in the existing prompt, and expressing the task more precisely to LLM. The complex reasoning capabilities of LLMs can be elicited by prompting the model to "think step by step" (Wei et al., 2022a; Kojima et al., 2022), and can be increased by instructing them to

Large Language Models like OpenAI's ChatGPT are trained on enormous text corpora, including books, journals, and web pages, which allows them to develop a comprehensive understanding of language structure, semantics, and context. LLMs can use this information to generate human-like replies in text form and provide great insights across many areas of NLP. ChatGPT has received a lot of attention and adoption in the industry, reaching one million subscribers in only five days, faster than Facebook and Instagram did to achieve the same milestone.

### **Prompt Engineering**

Humans give indications to LLMs to speak to. Prompt engineering (PE) is an emerging profession that seeks to create and refine prompts to successfully leverage large language models (LLMs) to yield desirable, relevant, and accurate outputs (Brown et al., 2020). So, the query needs to be phrased in a way that the model can best complete the task and provide the most helpful results. The phrase "Prompt Engineering" was popularized in an online post about the large language model GPT-3 and was then codified by Liu et al. (2023). PE is vital to improve communication with LLMs. Clear and unambiguous prompts are likely to yield appropriate solutions to desired queries, while more detailed verbs are likely to produce more

variable results (Bowen et al., 2020). Prompt engineering is the process of finding of prompting patterns and best practices to help the LLM to provide accurate responses (Wang et al., 2024). The need to learn this ability was highlighted by Knoth et al. (2024) especially to prevent the hallucination of ChatGPT being able to provide wrong or nonsensical responses. They have stressed that prompt engineering is fundamentally based on a reciprocal relationship between humans and AI, and that students need to edit prompts iteratively to improve the quality of prompts.

Physical Education is being increasingly emphasized in academic environments to improve the learning experience and is believed to offer tremendous potential for both educators and learners. Eager and Brunton (2023) argue that teachers should learn to write prompts that are aligned with learning objectives, allowing for the generation of bespoke content and assessments. For example, with few-shot learning, teachers can provide a huge language model with examples of quiz questions and ask it to generate similar content for their class. In addition, teachers can use chain-of-thought prompting to generate feedback that helps students to solve difficult difficulties step by step, thus improving their understanding. Bozkurt and Sharma (2023) explain how PE can be used by educators to develop resources such as lecture notes, case studies, and role-plays for use in classroom activities. Additionally, PE can foster critical thinking by prompting students to reflect on the biases and limitations of content produced by AI (Davis, 2025).

### **Prompt Engineering as 21<sup>st</sup> Century Skill for Learning**

The instructional value of emerging technologies is not only based on their technical features but also on their impact on learners' cognitive engagement, metacognitive monitoring, and self-directed inquiry. Research over decades has

demonstrated that students learn a lot and develop mastery as a skill when they are actively questioning, verifying their understanding, and revising their ideas through inquiry-driven engagement, rather than passively receiving information. The emergence of new artificial intelligence (AI) tools in learning environments poses a major challenge to understanding students' engagement with these technologies in terms of basic principles of active cognitive engagement and self-regulated learning.

Research on the effects of LLMs on student learning has yielded mixed findings regarding their impact on student involvement, academic performance, and motivation (Chiu et al., 2023; Grassini, 2023; Selwyn, 2022; Seo et al., 2021). Guo et al. (2025) did a research effort in STEM education and found that the use of LLMs improved the scientific knowledge, attitudes and problem-solving skills of middle school students significantly. In contrast, Jost et al. (2024) in a study in the setting of programming education found that more dependence on LLMs for critical thinking tasks like code generation and debugging was correlated with lower student grades. Similarly, Lehmann et al. (2024) carried out two pre-registered and incentivized laboratory experiments, showing that LLMs did not directly impact the learning outcomes.

However, exploratory analyses indicated that students' preexisting knowledge and LLM use influenced their learning with LLMs. For instance, students who asked LLMs to explain topics were found to have a better understanding of the topic, whereas students who asked LLMs for "solutions" to practice problems were able to cover a breadth of topics, but the depth of their understanding appeared to be less. Also, the research found that students with lower students with excellent prior topic knowledge learnt less with LLMs than with prior subject knowledge. This further underscores the natural complexity of the use of LLMs in traditional educational environments because they have the potential of assuming 2 different roles in

the learning process: complementation and substitution. Both are found to support learning, but students who use LLMs to complement their learning (asking for explanations) help deepen their understanding, while students who use LLMs as substitutes (asking for solutions) help cover more topic areas or volume of study material (Lehmann et al., 2024). Therefore, LLMs like ChatGPT might facilitate the learning process but also risk creating superficial learning and inhibiting critical thinking, problem-solving, and creativity skills (O'Connor, 2023). Both studies highlight that the use of LLMs in student learning is more advantageous as a supplementary learning tool, rather than complementary assistance (Jost et al., 2024; Lehmann et al., 2024). Zdravkova et al. (2024) explore the integration of LLMs into higher education by contrasting three different approaches: traditional/manual assignment creation without LLM support, full dependence on LLMs and a hybrid approach.

The study involving undergraduate students investigated preferences, happiness, productivity and comfort with these approaches across two types of assignments, essay writing and programming activities. Students preferred the mixed technique over traditional preparation or full dependence on LLMs, the results showed.

Most students saw LLMs as a useful tool for completing tasks, if they critically engage with the LLM output, pointing to the need for human supervision and involvement in the process. Similarly, Lepp and Kaimre (2025) explored the use of AI chatbots in a programming classroom by students and the connection between LLM usage and academic achievement. A student survey that examined how often and how LLMs were used found that the more often students reported using chatbot tools, the worse they tended to do in coursework, suggesting a negative correlation between students' academic performance and reported frequency of AI tools usage. Students who struggle with the course material and do not perform well may be more

inclined to use AI as a supplementary tool, which aligns with prior research indicating that low-performing students are more likely to seek out additional resources (Lepp & Kaimre, 2022). The study highlights the need to differentiate between the uses of LLMs by students, indicating that it is complementary rather than crucial to the students' learning process. Further, these findings emphasize the necessity of having a structured guideline and pedagogical framework that facilitates the proper integration of LLMs and AI tools in education, which encourages students' deeper learning and prevents over-reliance and dependence on LLM technology (Lepp & Kaimre, 2025).

#### **Education 5.0**

Education 5.0 is a significant part of the fifth industrial revolution that has the capacity to enhance the entire learning experience through the deployment of advanced technological tools. It is about the digital techniques used in Education 4.0. According to Education 5.0 (Ahmad et al., 2023), Large Language Models (LLMs) are viewed as a critical development in providing personalized educational experiences to meet the needs of individual learners. No technology or method before this has been able to provide this level of tailored education. However, the absence of AI literacy is a major obstacle to the complete implementation of Education 5.0. The potential of achieving AI literacy is receiving increasing attention from both learners and instructors, because of its tight connection to quality of the outcomes generated by LLMs (Knoth et al., 2024).  
Question:

Engineering is a core part of AI literacy and involves the creation and improvement of inputs to LLMs. The systematic investigation of different prompting tactics remains mostly unexplored. According to Oppenlaender et al. (2023), this quantitative study is important, as it would improve students' skills in AI, so that they can use LLMs such as ChatGPT more effectively.

Learners employ LLMs like ChatGPT to help write essays (Bernabei et al., 2023), develop scenarios (Bai et al., 2024), generate programming code (Chen et al., 2023), provide translations (Bernabei et al., 2023; Stojanov et al., 2024), summarize complex texts (Bernabei et al., 2023; Kasneci et al., 2023), and offer detailed critiques on their work (Kasneci et al., 2023; Qadir, 2023).

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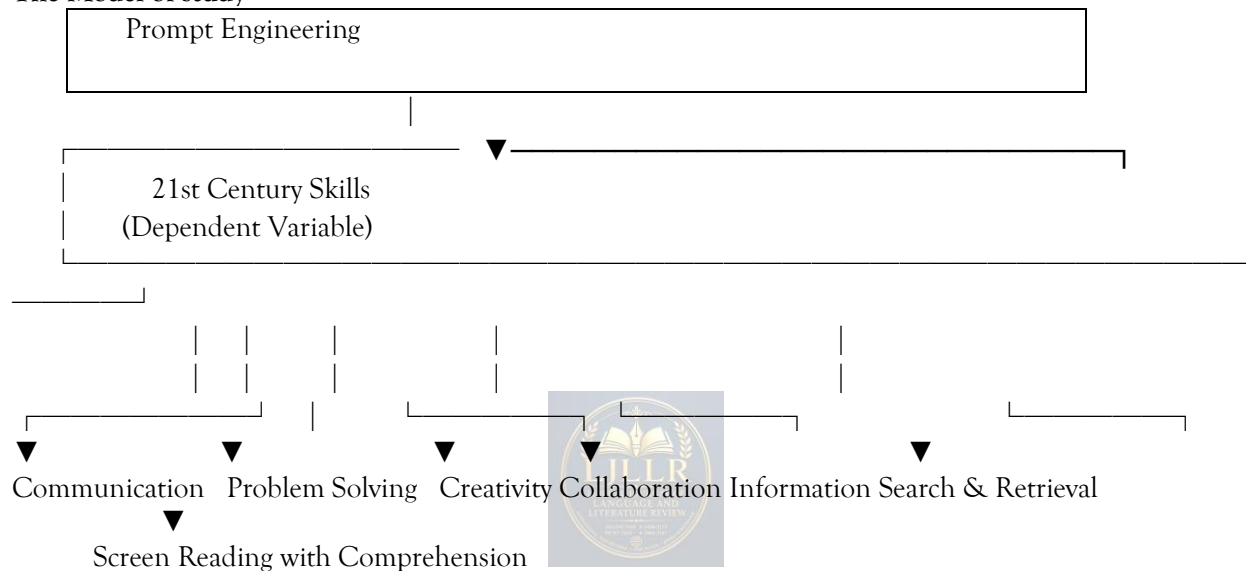
#### **Research Methodology**

The study employed a quantitative cross-sectional survey design to investigate undergraduate students' perspectives of prompt engineering as a 21st-century skill. The survey was conducted in four universities in Sindh, Pakistan, comprising public and private higher education institutions. These universities included The University of Mirpurkhas, Sindh Madressatul Islam University (SMIU), SZABIST University, Karachi and Salim Habib University, Karachi. The intended population was the undergraduate students from non-computing disciplines. They were enrolled in Education, Social Development, Business Administration, Environmental Sciences, English and Commerce to ensure they had no formal academic background in AI related disciplines. Data were acquired from 100 undergraduate students utilizing a standardized questionnaire through Google survey forms. The test was split into two sections. The first half gathered demographic information, and the second part included measures to assess participants' awareness, use, perceptions, and perceived significance of prompt engineering. Responses were recorded on a 5-point Likert scale ranging

from 1 (Strongly Disagree) to 5 (Strongly Agree). Participants volunteered to be included and provided informed consent before data collection. The acquired data were coded and analyzed using SmartPLS. Descriptive statistical techniques such as means, and standard deviations were used to provide an overview of the replies and to analyze

the trends of students' impressions of prompt engineering. The study was conducted by following ethical guidelines by preserving anonymity and confidentiality of the participants, without collecting any personally identifiable information, and using the data only for academic research.

### The Model of study



*Fig 1. The model of the Study*

### Research Model Conceptual

The conceptual model of this study was proposed by Prompt Engineering as an independent variable and 21st-Century Skills as a dependent variable. Prompt engineering is the capacity of students to efficiently design, improve and optimize prompts when dealing with generative artificial intelligence (AI) systems to produce accurate, relevant and meaningful results. The dependent variable 21st-century skills are conceptualized as a multidimensional construct, with six interrelated dimensions: communication skills, problem-solving skills, creativity, collaboration for academic projects, information search and retrieval, and screen reading with comprehension. The model presumes that students who are more

adept in prompt engineering are more likely to exhibit more competency in these core 21st-century abilities. Therefore, the study hypothesizes the favorable effect of prompt engineering on each of the six aspects as a potential basic digital skill for successful learning, critical thinking, collaboration and information literacy in higher education. As shown in Figure 1, the conceptual model of the investigation is proposed.

### Results

**Demographic Characteristics of the Participants.** The sample of this study was comprised of 100 undergraduate students from four public and private sector universities of Sindh. The participants were from different demographic

backgrounds, in terms of age, gender, university and discipline. Those who were studying Computer Science, Information Technology, Artificial Intelligence, Software Engineering and

other computing-related studies were excluded from the study. The demographic characteristics of the respondents are shown in Table 1.

| Demographic Variable | Classification                   | Frequency (f) | Percentage (%) |
|----------------------|----------------------------------|---------------|----------------|
| Gender               | Male                             | 46            | 46.0           |
|                      | Female                           | 54            | 54.0           |
| Age Group            | 18–20 years                      | 38            | 38.0           |
|                      | 21–23 years                      | 51            | 51.0           |
|                      | 24 years and above               | 11            | 11.0           |
| University Sector    | Public Sector (Sindh)            | 58            | 58.0           |
|                      | Private Sector (Sindh)           | 42            | 42.0           |
| Academic Discipline  | Social Sciences                  | 32            | 32.0           |
|                      | Business & Management            | 28            | 28.0           |
|                      | Arts & Humanities                | 22            | 22.0           |
|                      | Natural Sciences (Non-Computing) | 18            | 18.0           |

| Construct Level        | Latent Variable / Dimension | Cronbach's $\alpha$ | Composite Reliability (CR-rho_c) | Average Variance Extracted (AVE) |
|------------------------|-----------------------------|---------------------|----------------------------------|----------------------------------|
| First-Order Predictor  | Prompt Engineering (PE)     | 0.842               | 0.887                            | 0.612                            |
| First-Order Dimensions | Communication Skills (COM)  | 0.815               | 0.879                            | 0.593                            |
|                        | Problem-Solving Skills (PS) | 0.803               | 0.871                            | 0.576                            |

| Construct Level     | Latent Variable / Dimension   | Cronbach's $\alpha$ | Composite Reliability (CR-rho_c) | Average Variance Extracted (AVE) |
|---------------------|-------------------------------|---------------------|----------------------------------|----------------------------------|
|                     | Creativity (CR)               | 0.861               | 0.906                            | 0.707                            |
|                     | Collaboration (COL)           | 0.794               | 0.866                            | 0.565                            |
|                     | Info Search & Retrieval (ISR) | 0.833               | 0.889                            | 0.617                            |
|                     | Screen Reading (SRC)          | 0.820               | 0.882                            | 0.601                            |
| Second-Order Target | 21st-Century Skills (21CS)    | 0.912               | 0.931                            | 0.692                            |

#### Discriminant Validity (HTMT Criterion)

The Heterotrait-Monotrait (HTMT) ratio was computed to verify discriminant validity. All values listed in Table 4 fall beneath the strict 0.85 threshold, proving that the constructs are distinct from one another.

**Table 4: SmartPLS Discriminant Validity (HTMT Results)**

| Latent Constructs | 1. PE | 2. COM | 3. PS | 4. CR | 5. COL | 6. ISR | 7. SRC |
|-------------------|-------|--------|-------|-------|--------|--------|--------|
| 1. PE             | —     |        |       |       |        |        |        |
| 2. COM            | 0.512 | —      |       |       |        |        |        |
| 3. PS             | 0.584 | 0.461  | —     |       |        |        |        |
| 4. CR             | 0.473 | 0.509  | 0.533 | —     |        |        |        |
| 5. COL            | 0.411 | 0.598  | 0.427 | 0.491 | —      |        |        |
| 6. ISR            | 0.556 | 0.442  | 0.501 | 0.466 | 0.382  | —      |        |
| 7. SRC            | 0.498 | 0.487  | 0.479 |       |        |        | —      |

The bulk of the participants, as indicated in Table 1, were 21–23 years old (47.7%,  $n = 31$ ), followed by 18–20 years old (36.9%,  $n = 24$ ) and 24–26

years old (15.4%,  $n = 10$ ). The sample included 35 male students (53.8%) and 30 female students (46.2%). The participants were selected from four

universities of Sindh, The University of Mirpurkhas (27.7%), Sindh Madressatul Islam University, Karachi (26.2%), SZABIST University, Karachi (24.6%) and Salim Habib University, Karachi (21.5%). Academically, the respondents

came from several non-computing fields. The highest share of the respondents was from Business Administration (27.7%), followed by English (20.0%), Education (18.5%), Social Sciences (18.5%) and Commerce (15.4%).

### *Measurement Model Evaluation*

| Construct Variable                      | Level / Latent | Cronbach's $\alpha$ | Composite Reliability (CR) | Average Variance Extracted (AVE) |
|-----------------------------------------|----------------|---------------------|----------------------------|----------------------------------|
| <b>First-Order Predictor</b>            |                |                     |                            |                                  |
| Prompt Engineering (PE)                 |                | .842                | .887                       | .612                             |
| <b>First-Order Dimensions</b>           |                |                     |                            |                                  |
| Communication Skills (COM)              |                | .815                | .879                       | .593                             |
| Problem-Solving Skills (PS)             |                | .803                | .871                       | .576                             |
| Creativity (CR)                         |                | .861                | .906                       | .707                             |
| Collaboration (COL)                     |                | .794                | .866                       | .565                             |
| Information Search & Retrieval (ISR)    |                | .833                | .889                       | .617                             |
| Screen Reading with Comprehension (SRC) |                | .820                | .882                       | .601                             |
| <b>Second-Order Target Construct</b>    |                |                     |                            |                                  |
| 21st-Century Skills (21CS)              |                | .912                | .931                       | .692                             |

### **Structural Model Analysis and Hypothesis Testing**

Following the measurement model assessment, a bootstrapping procedure with 5,000 resamples was

run in SmartPLS to evaluate the structural relationships and determine the significance of the path coefficients.

**Table 5**  
*Path Coefficients and Structural Hypothesis Testing*

| Hypothesis | Structural Path                                        | Path Coeff. ( $\beta$ ) | Standard Error (SE) | t-value | p-value | Decision  |
|------------|--------------------------------------------------------|-------------------------|---------------------|---------|---------|-----------|
| Primary    | PE $\longrightarrow$ 21st-Century Skills (Overall)     | .618                    | .058                | 10.655  | < .001  | Supported |
| H1         | PE $\longrightarrow$ [21CS] Communication Skills       | .501                    | .052                | 9.635   | < .001  | Supported |
| H2         | PE $\longrightarrow$ [21CS] Problem-Solving Skills     | .532                    | .055                | 9.673   | < .001  | Supported |
| H3         | PE $\longrightarrow$ [21CS] Creativity                 | .482                    | .049                | 9.837   | < .001  | Supported |
| H4         | PE $\longrightarrow$ [21CS] Collaboration for Projects | .451                    | .046                | 9.804   | < .001  | Supported |
| H5         | PE $\longrightarrow$ [21CS] Info Search & Retrieval    | .507                    | .053                | 9.566   | < .001  | Supported |
| H6         | PE $\longrightarrow$ [21CS] Screen Reading w/ Comp.    | .494                    | .051                |         |         |           |

The results in Table 5 reveal that Prompt Engineering has a significant positive direct influence on the higher-order 21st-Century Skills construct (beta = .618,  $t = 10.655$ ,  $p < .001$ ). Hypotheses H1 to H6 followed the higher-order

design to test the total effects of prompt engineering on each sub-dimension. All six specific sub-hypotheses were supported as the route coefficients ranged between .451 and .532, and all were statistically significant at  $p < .001$ .

*Item-Level Descriptive Statistics for Constructs*

| Construct                      | Item | Questionnaire Statement                                                                                 | Mean | (SD) |
|--------------------------------|------|---------------------------------------------------------------------------------------------------------|------|------|
| <b>Prompt Engineering (PE)</b> | PE1  | I systematically structure my prompts to get precise outputs from AI tools.                             | 3.84 | 0.82 |
|                                | PE2  | I iteratively change and refine my prompts when the first AI response is insufficient.                  | 3.91 | 0.76 |
|                                | PE3  | I critically evaluate AI-generated content before using it in my academic work.                         | 3.76 | 0.89 |
|                                | PE4  | I use advanced optimization tactics (such role-assigning or few-shot examples) to increase output.      | 3.68 | 0.81 |
|                                | PE5  | I am aware of AI ethics and biases when I prompt.                                                       | 3.95 | 0.74 |
| <b>Communication (COM)</b>     | COM1 | AI prompts help me to get my assignments and essays perfectly.                                          | 4.08 | 0.68 |
|                                | COM2 | My written communication and use of vocabulary have improved with the use of AI.                        | 4.05 | 0.72 |
|                                | COM3 | I can quickly tailor the difficulty of a text with AI for different audiences.                          | 3.93 | 0.73 |
| <b>Problem-Solving (PS)</b>    | PS1  | I utilize AI to take complicated academic challenges and break them down into small manageable chunks.  | 3.94 | 0.75 |
|                                | PS2  | Interactive brainstorming with AI helps me to discover alternative solutions to study related problems. | 3.85 | 0.80 |
|                                | PS3  | AI technologies help me to find weaknesses or holes in my own logic.                                    | 3.88 | 0.79 |

| Construct                     | Item | Questionnaire Statement                                                                                         | Mean | (SD) |
|-------------------------------|------|-----------------------------------------------------------------------------------------------------------------|------|------|
| Creativity (CR)               | CR1  | AI prompt helps me produce new ideas and unique concepts for my tasks.                                          | 4.16 | 0.64 |
|                               | CR2  | I use AI to analyze the day-to-day class assignments from a novel perspective.                                  | 4.04 | 0.73 |
|                               | CR3  | AI prompts help me to present my presentations with more creative visual slides.                                | 4.13 | 0.70 |
| Collaboration (COL)           | COL1 | I use oftenly AI prompts to do my group tasks and delegate responsibilities for projects related to my classes. | 3.86 | 0.86 |
|                               | COL2 | AI tools and prompts help me to brainstorm ideas and present in novel manner.                                   | 3.98 | 0.79 |
|                               | COL3 | Prompting AI helps me draft reports, assignments and projects with my partners and teachers.                    | 3.92 | 0.84 |
| Info Search & Retrieval (ISR) | ISR1 | I can locate relevant academic sources and summaries much faster by using AI.                                   | 4.21 | 0.61 |
|                               | ISR2 | Phrasing specific prompts helps me extract precise data points from large reference materials.                  | 4.14 | 0.66 |
|                               | ISR3 | AI tools help me filter out irrelevant search results during my literature reviews.                             | 4.10 | 0.68 |
| Screen Reading (SRC)          | SRC1 | I can comprehend long, complex digital articles better when using AI text summaries.                            | 3.78 | 0.83 |
|                               | SRC2 | AI tools help me maintain my reading focus on a screen by highlighting core concepts.                           | 3.66 | 0.88 |
|                               | SRC3 | I am able to skim digital research papers more effectively without losing critical meaning.                     |      |      |

Descriptive statistics were used to analyze each item to determine the students' self-assessment of their proficiency in prompt engineering and the use of 21st-century abilities. Table 2 presents the means and standard deviations at the item level using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Overall, participants had a good opinion of applying AI in academic objectives with all categories having mean scores above the mid-point of 3.0. The most trust in prompt engineering was in students' grasp of ethical AI bounds and biases ( $M = 3.95$ ,  $SD = 0.74$ ) and their ability to iteratively improve prompts ( $M = 3.91$ ,  $SD = 0.76$ ). The lowest score in this category ( $M = 3.68$ ,  $SD = 0.81$ ) was for the item on the use of advanced optimization strategies, e.g., few-shot prompting, indicating students may be less familiar with more technical prompting techniques, but comfortable with basic iterative adjustments. The most agreement between participants was in items related to Information Search and Retrieval as a 21st-century ability, namely, the speed of access to academic sources ( $M = 4.21$ ,  $SD = 0.61$ ). Similarly, we found strong engagement for items in the Creativity dimension with participants noting that AI helps them develop new ideas ( $M = 4.16$ ,  $SD = 0.64$ ). The dependent variables with the lowest means were connected to Screen Reading with Comprehension, namely, to employ AI to stay focused when reading on a screen ( $M = 3.66$ ,  $SD = 0.88$ ). The finding indicates that although AI is considered very useful in searching and creative brainstorming, students say there is a substantial hurdle in using the technology to assist with sustained digital reading comprehension.

### Discussion

The main objective of this study was to explore the impact of prompt engineering on the 21st-century skills of undergraduate students in a non-computing discipline. The analysis of the structural model provided good empirical support

for the general research idea. The research revealed a substantial and favorable direct effect of timely engineering on the higher order 21st century skills construct ( $\beta = .618$ ,  $t = 10.655$ ,  $p < .001$ ). The primary hypothesis and all the six sub-hypotheses (H1 to H6) were supported. The model demonstrated promise in its explanatory power, accounting for 38.2% of the variation ( $R^2 = .382$ ) in students' overall 21st-century skills. The results show that systematic engagement with AI tools through fast engineering is a substantial driver for the development of broader academic skills, especially for students without a typical computer science background. The descriptive data proceeded to the areas of agreement at the highest levels of information search and retrieval and originality. Specifically, the greatest score of the students was for one item linked to applying AI to locate important academic references and summaries considerably faster ( $M = 4.21$ ,  $SD = 0.61$ ). This is also evidenced by the relevance of H5 ( $\beta = .507$ ,  $p < .001$ ) showing that prompt engineering fosters digital research operations. Similarly, high scores on creative features such as the ability to produce fresh ideas for projects ( $M = 4.16$ ,  $SD = 0.64$ ) are associated with the adoption of H 3 ( $\beta = .482$ ,  $p < .001$ ). Results reveal that students without computers quickly embrace AI as a collaborative partner, fast browse literature and start brainstorming, and transform abstract problems into immediately useful academic ideas. Conversely, the highest scores were recorded in the dimensions of screen reading with comprehension and advanced optimization tactics in the current study. The students did not agree as much about employing AI to enable them to keep focused on reading on a digital screen ( $M = 3.66$ ,  $SD = 0.88$ ). H6 was statistically supported ( $\beta = .494$ ,  $p < .001$ ). However, the lower means reveals that artificial intelligence (AI) technologies assist in comprehending digital text but may not entirely relieve the cognitive weariness of extended screen time. Students also reported the least engagement

with advanced optimization tactics such as few-shot prompting ( $M = 3.68$ ,  $SD = 0.81$ ) across the independent variable items. That means undergrads do some basic/commonsensical prompt engineering but not formally trained in advanced prompt engineering skills. Future online literacy education must therefore be designed to fill this gap and enable students to shift from casual AI use to more complicated optimization.

### Findings

This study on the application of fast engineering to improve academic skills for undergraduate students in non-computing majors obtained three key findings: Enhanced Academic Skills via Prompt Engineering The conclusion is that a student's ability to develop and edit AI prompts is connected to his or her overall 21st-century competencies. Students that use artificial intelligence (AI) tools often show large gains across all six areas studied: communication, problem-solving, creativity, cooperation, information retrieval and digital reading comprehension. Fast engineering is more than an engineering shortcut. It is a great instrument for the evolution of general intelligence.

**Student Benefits:** Research and brainstorming velocity the important thing for pupils was that AI might speed up their research and provide them with fresh ideas. Students said AI was excellent for finding academic sources rapidly, summarizing large amounts of reference material and producing new ideas or visual outlines for assignments. AI is a good partner for students who are not tech-savvy to get over writer's block and to deal with massive amounts of content.

**Advanced Methods and Limitations of Screen Fatigue** However, the research did highlight some important limitations in the ways in which kids are currently using the technology. Most students are left with basic trial and error prodding and cannot use higher optimization tactics such as role assignment or structural constraints. AI-generated

summaries also help to structure information, but they do not solve the problem of digital screen fatigue. But when kids read long materials on a computer screen, they have problems concentrating and understanding.

Study suggests few recommendations like, firstly, universities need to offer quick hands-on training to non-computing majors on sophisticated prompting skills that transcend simple trial-and-error techniques. Secondly, educators need to develop activities that mix AI-generated summaries with hands-on, offline practice because screen-reading fatigue is a significant hurdle. Thirdly, universities need to draw clear lines between using AI to stimulate creative thinking and utilizing it as a tool for academic dishonesty. Fourthly, teachers need to design projects that push students to critically assess, and challenge knowledge produced by AI rather than accepting it at face value and to foster problem-solving, not shortcuts.

### Conclusion

Results from this study demonstrate that prompt engineering, as a crucial enabler of 21st century academic skills, can be beneficial to undergraduate students in non-computing areas. The findings suggested that re-conceptualizing the purposeful and deliberate use of AI from discrete skills to an integrated higher-order construct may significantly influence students' abilities to retrieve information, generate unique ideas, and solve academic problems.

But the figures show a big gap too. Students are looking to use AI to cut corners on their research, but they're still dealing with digital screen fatigue and don't know how to apply complex prompt optimization tactics. Ultimately, generative AI is not a substitute for critical thinking, but a collaborative tool that requires deliberate directing. Formal non-technical AI literacy should be included in the curriculum of the higher education institutions in Sindh to enable the undergraduate students to deal with the digital

needs of today's academic environment successfully and ethically.

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