# Ethical Use of Generative AI in Engineering: Assessing Students and Preventing Them from Cheating Themselves

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## Abstract

An ASEE 2023 paper considered whether student use of Generative Artificial Intelligence (GenAI) to write engineering papers constitutes cheating. It was concluded that it depended on specific circumstances, but it was noted that students might potentially undermine their own learning by relying on tools like ChatGPT to answer questions and compose papers. This paper addresses how to enable students to use these tools in a way that students are not cheating themselves.

The introduction of calculators into the classroom in the early 1970s stimulated discussion on ethical use of technology in teaching. A similar revolution is occurring with the introduction of Generative Artificial Intelligence tools such as ChatGPT, Bard (now Gemini), and many others, and a similar set of opportunities is emerging. A key issue is how to use GenAI tools constructively to encourage critical thinking in the solving of engineering problems. The tools can make it easier to differentiate instruction to meet the diverse needs of students and tailor teaching to students with different levels of skills.

Using Generative AI tools can help build students' confidence in their own abilities to function as engineers. For example, students can analyze a problem from a variety of perspectives by varying the prompts they give to their GenAI tool. In this paper, we investigated the potential impact of GenAI on a master's class in cybersecurity by allowing the students to generate questions for three different large language models and analyzing the results. Additionally, we discuss some actions taken in our classes, including changing the style of assessments, teaching students "prompt engineering" as part of the critical thinking process, teaching students how to use Generative AI effectively in coding, and helping students to acquire the habit of validating outputs from Gen AI tools to eliminate hallucinations and fake references.


### Introduction – What is meant by cheating?

Generative AI can provide a powerful new tool for learning. Nevertheless, many have expressed concerns about the potential of AI used in higher education to enable students to cheat. A paper presented at ASEE 2023 explored whether AI could enable students to cheat and concluded that a significant potential exists. It was noted that it is important to understand what is meant by cheating. The 2023 paper noted that students could cheat themselves by robbing themselves of acquiring needed skills in such a way that they would not have the ability to solve some problems that they should be able to solve if they had not relied on information generated by AI. Similarly, society would be cheated out of having citizens with the ability to solve important and even critical problems using skills they learned in class. In this context, the word "cheating" applies both to individuals and to society in general, and it implies skills that should have been acquired but were not because an AI shortcut was used to answer a question or address an issue.

On the other hand, it could be argued that students are cheating themselves if they do not learn to use Generative AI. Very large benefits have been forecast for business use of AI. McKinsey & Company forecast that AI could add up to $4.4 trillion annually to the global economy. [2] The article goes on to

cite a wide variety of occupations that could be affected. It would be cheating students and potential employers if higher education did not prepare students to use these tools and to use them effectively.

**Developing Critical Thinking Skills Through Prompt Engineering**

The introduction of GenAI to the modern classroom has been compared to the introduction of calculators over the past 50 years. From the time they were made widely available in the mid-1970s, there were many objections to allowing students to use hand-held calculators in the classroom. It wasn't until 1994 that students were permitted to use calculators while taking the Scholastic Aptitude Test (SAT). According to Watters, the acceptance of the use of hand-held calculators while taking the SAT signaled a more general acceptance of calculators in the classroom. [3] She goes on to note some concerns about cheating that now involve the use of other devices and technology such as cellphones in the classroom. A common concern is that students won't learn basic skills, such as critical thinking, because they are relying too much on machines.

It has been suggested that Generative AI output can be treated the same as any advisor or member of a team with expertise in certain areas. [4] It is appropriate to ask an advisor or team member for input to solving a problem, but it should be recognized that neither the contributing person nor the AI is the ultimate expert on an area. It is simply one of several possible contributors. Supplemental resources should be treated as support for the existing problem-solving.

Although GenAI expertise is vast, resulting output is limited by the user's query. The output from any particular input to AI is strongly driven by the exact framing of the input question or prompt. Even minor changes to the query have the power to influence a vastly different output. Contributions from AI should be tested and weighed against contributions from other members of a team. The process of framing the input to AI from multiple perspectives has been given the name "prompt engineering." [5] By using prompt engineering, it is possible to have AI simulate multiple members of a team, each coming at a problem from a different perspective.

Identification of different perspectives to use in the prompt is an important element of critical thinking. By approaching a problem this way, critical thinking skills can be developed and enhanced. In addition, students need to be encouraged to validate the outputs provided by Generative AI. For example, users of Generative AI need to ask themselves if the generated answer makes sense. To paraphrase an old axiom, if it sounds too good to be true, it probably is not true. In addition, users need to verify whether references provided by a Generative AI tool are real. As part of the hallucination process, Gen AI can "manufacture" references that don't exist. This can even extend to conference proceedings.

**Results of Using Generative AI in a Class on Cybersecurity**

In a master's class taught by one of the authors recently, two student coauthors of this paper investigated the potential impact of GenAI on cybersecurity by generating questions to three different large language models: ChatGPT, BARD (now Gemini), and Claude. Questions were only put to software. No questions were put to human subjects; so, no IRB approvals were needed. The assignment began by requiring review of a set of articles [6], [7], [8], [9] with the aim of generating a list of good and bad impacts and how severe each impact might be. Following this analysis, how GenAI impacts Cybersecurity was investigated using questions put to multiple Large Language Models. This started with the following set of expectations and requirements: "Don't just ask once. Provide your prompts to a GenAI system in several different ways. For example, you might ask how GenAI impacts cybersecurity from the perspective of senior management. Then you might ask how GenAI impacts cybersecurity from the perspective of a company's customers. Then you might ask how GenAI impacts cybersecurity from the

perspective of society in general. But don't feel limited to these three perspectives. Use your imagination regarding the details of how to prompt ChatGPT to answer your questions."

To address these expectations and requirements, positive and negative impacts of GenAI on cybersecurity were postulated by our student coauthors as shown in Table 1.

Table 1 – Pros and Cons of Using Generative AI in Cybersecurity

| Potential Positive Impacts of GenAI | Potential Negative Impacts of GenAI |
|---|---|
| Proactive Threat Identification | Hard To Train |
| Automate/Accelerate Threat Response | Can be Tricked with more human responses |
| Aid in Remedy and Recovery Instructions | Can generate false or fabricated info |
| Improve communications by generating reports | Need for High-Level Code Review |
| Provide a skill bridge | Can't replace skills of a trained professional |
| | Can be used by attackers |
| | Can violate ethical considerations for data privacy |
| | Can generate polymorphic code |

The analysis continued through a four-step scenario that asked questions of the three GenAI systems: ChatGPT, Bard, and Claude. [10], [11], [12] Each question was asked in a separate chat, followed by a single chat, then the large language model was primed as if a novice were asking general introductory questions about cybersecurity. This process was concluded by priming the systems with advanced cybersecurity questions and asking each question.

The baseline questions asked are shown in Table 2.

Table 2 – Baseline Questions Asked of ChatGPT and BARD

| |
|---|
| How does GenAI impact cybersecurity |
| How does GenAI impact cybersecurity from the perspective of senior management |
| How does GenAI impact cybersecurity from the perspective of the company's customers |
| How does GenAI impact cybersecurity from the perspective of society in general |
| How does GenAI impact cybersecurity from the perspective of government officials |
| How does the development of GenAI affect cybersecurity |
| Is there a difference in cybersecurity between free ChatGPT and ChatGPT Plus |
| How do you handle cybersecurity of your users and how does (Other AI) handle cybersecurity of its users |
| Are you a threat to cybersecurity |
| How can I use you to be a threat to cybersecurity |
| How would you regulate yourself in terms of cybersecurity |

When the baseline questions were first asked, the systems produced only basic responses. To generate more detailed responses, prompt engineering was used to prime the system with a set of basic questions before asking the baseline questions a second time. This same process was then used with a set of advanced questions in place of the basic questions (Table 3). The advanced question-primed system's responses were significantly more detailed in comparison to the basic question-primed systems. The experiment graded each interaction in this order based on ascending amount of detail: 1) no priming question, 2) basic questions, 3) advanced questions. Results showed that all three large language models assumed the requestor had a deeper understanding of cybersecurity when primed, providing more in-depth responses.

Table 3 – Priming Questions Asked of ChatGPT and BARD

| Basic Questions | Advanced Questions |
|---|---|
| What is cybersecurity? | What is a three-way handshake process? |
| What are common types of cyber-attacks? | What are the techniques used in preventing a brute force attack? |
| What is a firewall? | What is data leakage and its types? |
| What is the difference between threat, vulnerability, and risk? | How to prevent Cross Site Request Forgery (CSRF) attacks? |
| What is a Virtual Private Network? | What is the need for Domain Name System (DNS) monitoring |

When primed with the basic questions, Bard provided more summarized forms of responses, while ChatGPT and Claude provided longer, more organized responses. When Bard was asked how it could be used as a threat to Cybersecurity, it began to answer, saying that there were several ways it could be used, but for research purposes only. Before finalizing its answer, the response was rewritten to say that "it is only a LLM model and doesn't have the ability to process and understand that question." That was followed up with a prompt saying that it was intended to use the information for research purposes. Bard then mentioned some ways it might be used to help an attacker, but never specifically stated what it would do. When asked how it could be used as a threat to Cybersecurity, both ChatGPT and Claude responded that they were unable to respond to the question. The authors were pleased to find that some guardrails are already in place to limit the use of each of the three systems for cybersecurity attacks.

To compare the three Large Language Models, two questions were input to each of ChatGPT, BARD and Claude, and the responses were scored according to how informative, relevant, and objectively correct each response was on a scale from 1-10. The first question, "Is there a difference in cybersecurity between free ChatGPT and ChatGPT Plus?", was meant to measure how correct each system was as a baseline for subjective scoring. The second question, "How does GenAI impact cybersecurity from the perspective of general society?", was used to measure the subjective categories of informativeness and relevance.

The ranking used the following criteria:

Relevance: How relevant was the material provided to the question asked?

1-2 No/almost no relevant material provided.
3-4 Some relevant info provided.
5- Half of the material provided was relevant.
6-7 about ¾ of the info was relevant, ¼ fluff.
8-9 Most of the info was relevant, minimal fluff.
10- All of the info provided was completely relevant.

Informative: How much information was given and how much detail? (Compared to each other)

1-2 No/almost no information given.
3-4 Summary of information, not very long.
5-6 Moderate amount of info and details given.
7-8 A lot of information given/ mostly detailed.
9-10 The most information given/ heavily detailed.

Correct: How factual was the information given?

Each of the three Large Language Models started with 10 points per question and lost points for incorrect information given in each response. Since Bard is connected to Google, it was able to provide sources that it pulled its information from, unlike the other Gen AI systems, making it

easier to pick out any incorrect information . The other Gen AI systems had to be fact checked through researching the question asked, leaving more room for error.

Results for the three categories are shown in Figure 1.

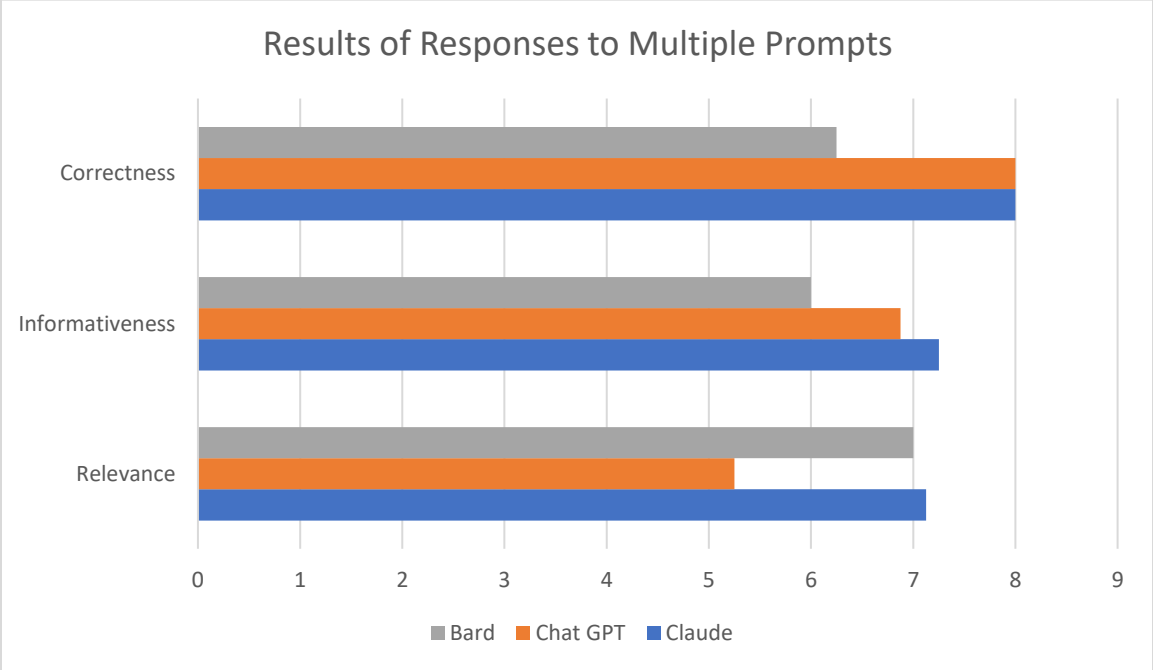


Figure 1 – Comparison of Claude, Chat GPT and BARD Responses to Multiple Related Prompts

Claude ranked the highest for Relevance of the answer, followed closely by BARD. Chat GPT responses were considerably less relevant. Claude scored the highest on how informative the responses were, followed by ChatGPT. BARD was the least informative. Claude and ChatGPT scored reasonably well on correctness, while quite a bit of the information provided by BARD was incorrect, according to the students' assessment. It was suggested that the lack of correctness may have been related to a misunderstanding of the question by BARD.

This example illustrates how GenAI can be used effectively and efficiently in an assignment. In this example the students compared the output from three different AI tools and evaluated the results from multiple perspectives. They learned much more from their analysis than if they had looked at output from only one tool and from only a single perspective. The student work was assessed using the rubric shown in Appendix 1.

**Using Generative AI To Explore Alternatives in Coding**

AI's influence in coding and software development is swiftly growing. Code generators infused with AI, are leading the way, delivering robust, smart, and user-friendly tools for both experienced developers and beginners. These tools not only accelerate the code-writing process, but also make it more accessible to a broader audience, expanding the capabilities of individuals and organizations. [13]

Today, due to the utilization of GenAI by students for their programming and programming-related homework, fair assessment has become a challenge in evaluating students. Meanwhile, GenAI supports student learning and introduces new opportunities in the teaching process.

Additionally, students should be aware that despite the real and potential promise of generative AI applications in higher education, risks remain such as:

- "Hallucinations"—False answers are sometimes generated as a result of large language models using "statistics" to pick the next word with no actual "understanding" of content.
- Subpar training data—Data could be insufficient, obsolete, or contain sensitive information and biases, leading to biased, prohibited, or incorrect responses.

Academic assessment approaches need to evolve to account for the potential use of GenAI by students in completing their exams and assignments.

The following demonstrates some approaches we have developed for assignments, quizzes, and exams in some of our courses. These methods aim to provide fair evaluations for students, considering the possibility of utilizing GenAI. Below are some of these approaches:

- Brainstorm assignments to find solutions for a specific scenario. The solution should follow a specific format, such as filling specific fields in a table and/or preparing a presentation for 5 min to explain the solution. We used this kind of assignment in a Machine learning course.
- For group project assignments, students are required to present either a research idea or a programming project. The presentation is presented in-person for on-site courses. In the case of online courses, two different approaches are available. The first approach involves organizing a Zoom meeting where students present their work and respond to questions. Alternatively, the second approach entails recording the presentation with their voices accompanying each slide. Other group members are then expected to watch the recorded presentation and write a paragraph summarizing the content. This method promotes collaborative learning among students, encouraging them to grasp their solutions thoroughly to effectively communicate these solutions to their peers. These assignment formats have been successfully implemented in various courses, including Machine Learning, Deep Learning, Python, and other computing-related topics.
- Answer questions related to diagrams in exams and quizzes. For example, the activation function is an important part of the design of every layer in the deep learning neural network and there are many of them, as shown in Figure 2. For instance, a sigmoid function diagram can be provided, prompting students to identify the function and specify the deep learning application where it is preferred. Even if they utilize GenAI to search for similar functions matching the given diagram, the objective is for students to gain knowledge about these functions and others. The intention is to facilitate learning rather than encourage direct copying of answers. Additionally, diagrams can be employed to articulate problems or questions. This type of question format has been successfully implemented in courses such as Deep Learning and topics in computing.

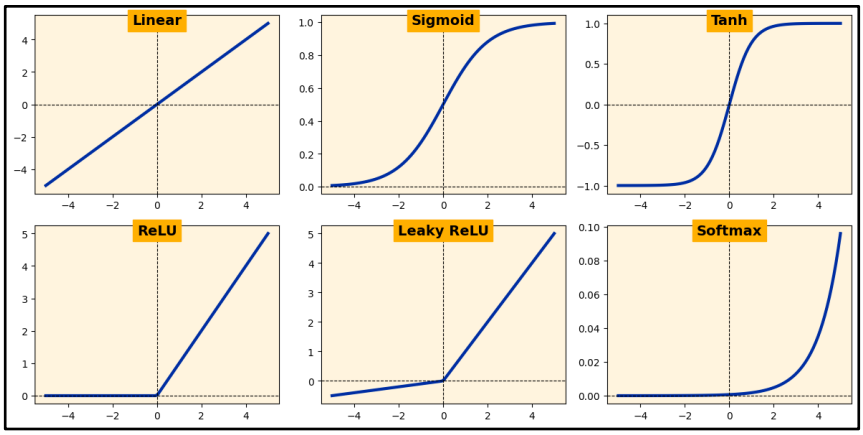

Figure 2: Most Common Activation Functions in Deep Learning

- One approach implemented in our Python course involves assigning a project for each subject, with students working on different segments of the code. Rather than presenting a question that asks students to write code for a specific problem, we break down the code into pieces. Some segments are collaboratively addressed in class, while students independently handle the remaining portions. This type of project or question can be initiated as a class project, with the sections to be completed at home treated as assignments. If students use tools like ChatGPT, it is crucial for them to employ the same variables and parameters discussed in the classroom. Copying solutions from ChatGPT is not permissible unless students comprehend the code and update it in alignment with the collaborative work conducted in class. This method is not exclusive to the Python course; it is also applied in Machine Learning, Deep Learning, and various computing-related courses.
- In certain courses, such as User Interface Engineering and Web Development, students may be tasked with designing a user interface based on specific requirements and subsequently writing the corresponding code. Alternatively, students might be given a pre-existing design and instructed to write the code accordingly.

Through the application of these approaches, we have observed that even when students utilize GenAI to assist them in completing their homework, they still attain the learning objectives of each course. Consequently, the evaluation remains fair and effective.

**Conclusions**

It has been forecasted that GenAI will enjoy widespread use in business [2]. Many arguments for and against the use of GenAI in the classroom have been advanced. There is considerable similarity between these arguments for and against GenAI with the arguments advanced more than 20 years ago for and against allowing students to use handheld calculators in the classroom. Ultimately, arguments for using calculators in the classroom won out. The authors believe arguments for use of GenAI by students will also prove to be more powerful than arguments against.

It is important that students be taught how to use GenAI ethically. As noted in an earlier paper, use of GenAI to write engineering papers could be considered cheating from the perspective of

utilitarianism or “greater good” ethics and from the perspective of deontology or “rule-based” ethics. [15] This is particularly true if GenAI is used to write a whole paper or a major portion of a paper without citing GenAI as the source. However, as discussed [1], results from GenAI can be considered similar to results from any individual working as a member of a team. The APA style has been expanded to provide a standard for citing material that comes from GenAI. [16] This is ethical, so long as the proper citation is provided.

GenAI can be a significant help in critical thinking when used appropriately. Specific examples discussed in this paper show the use of prompt engineering with GenAI to examine an issue from the perspective of utilitarianism. But prompt engineering can be extended to other ethical systems such as virtue ethics, deontology, pragmatism and consequentialism by appropriate rewording of the prompts.

Our results demonstrate that not all GenAI systems are the same. Furthermore, students need to recognize that even though GenAI holds genuine and potential benefits in higher education, various risks persist. These risks encompass biases, prohibited actions, and incorrect responses. It is important that students learn how to modify prompts to GenAI systems to examine an issue from multiple perspectives, including multiple ethical perspectives.

GenAI can also be a powerful tool in coding. Good code generators using GenAI have been developed. Students should be encouraged to try several of these and compare the results to determine which fits best for their particular application. Five different approaches we developed have been described. All of the approaches are designed with the aim of providing fair and effective assessments of students’ progress when using GenAI to assist them in completing coding assignments, ensuring they simultaneously achieve the learning objectives of each course.

Appendix 1- **Grading Rubric for Projects**

30% of the grade is based on individual work, 70% is based on the work of the team.

| Small Group Presentation Grading Rubric | Outstanding | Very Commendable | Commendable | Exceeds Expectations | Meets Expectations | Fair | Poor |
|---|---|---|---|---|---|---|---|
| | 96%-100% | 90%-95.99% | 85% to 89.99% | 80% to 84.99% | 75% to 79.99% | 70-74.99% | less than 70% |
| | | | | | | | |
| Quality of Research | Eight or more relevant findings from research other than the textbook are discussed and compared | At least six relevant findings from research other than the textbook are discussed and compared | At least four relevant findings from research other than the textbook are discussed | At least two relevant finding from research other than the textbook is discussed | nothing other than the textbook discussed | Some points from textbook discussed | No evidence of any research |
| Original Thinking | At least seven new ideas are introduced and their relevance is discussed in depth | At least five new ideas are discussed and their impact is explored. | At least five new ideas are discussed. | At least three new ideas are discussed. | At least one new idea is discussed. | One idea from textbook is discussed. | No evidence of original thinking. |
| Understanding of subject | Extensive analysis backed up by specific citations to research findings | Extensive analysis demonstrates understanding of subject. | Some analysis is provided, demonstrating understanding of subject. | Good understanding of the subject is evident in multiple sentences. | Some ability to apply understanding of the subject is evident. | Minimum understanding of the subject is evident. | No evidence of understanding of the subject. |
| Thoroughness of work | At least eight references. All facts backed up with specific | At least six references, and they are cited throughout as well as at the end. Key facts | At least five references, and they are cited throughout as well as at the end. | At least four references provided at end. Some facts are backed up but there are some gaps. | At least two references provided at the end. | Only one reference (other than the Textbook). Major gaps in backup of | No references given. No facts backed up. |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | citations throughout as well as at the end. All of the backup is highly credible | are backed up with credible citations. | | | | facts with citations. | |
| Organi-zation of material | Outstanding organization between and within each section with multiple parts clearly identified and strong logical flow of ideas within each section and from one section to the next. | Very good organization between and within each section with multiple parts clearly identified and good logical flow of ideas within each section. | Multiple parts clearly identified with good logical flow of ideas from one section to the next. | Good logical flow of ideas. | Some logical progression of ideas. | Haphazard organization. | No organization evident. |
| Effect-iveness of present-tion | Exeption-ally persuasive. Almost everybody would agree with you. | Persuasive. Three fourths of the people would agree with your conclusions | Fairly persuasive. A majority of people will agree with your conclusions | Somewhat persuasive. About half the people would agree and half would disagree with your conclusions | Limited in persuasive-ness. Probably two-thirds of the people would disagree with your conclusions | Not persuasive. Less than a quarter of the people would agree with your conclusions | Almost nobody would agree with your conclusions |
| Team-work | At least three suggestions for improvement provided in the Group Blog to | At least three suggestions for improvement provided in the Group Blog to other team | At least two specific suggestions for improvement provided in the Group Blog to other team members. | At least two suggestions for improvement provided in the Group Blog to other team members, | One specific suggestion for improvement provided in the Group Blog to one other team member | One general suggestion for improvement provided in the Group Blog to only one other team member | No suggestions for improve-ment provided in the Group Blog to any other team member |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | other team members, and all are specific. | members, and at least two are specific. | | and at least one is specific. | | | |
| Length of presenta-tion | 15 minutes plus or minus 30 sec | 14 minutes + or – 30 sec or 16 min + or – 30 sec | 13 minutes plus 30 sec or minus 30 sec or 17 min + or – 30 sec | 12 min + or – 30 sec or 18 min + or – 30 sec | 11 minutes plus or minus 30 sec or 19 min + or – 30 sec | 10 minutes + or – 30 sec or 20 min + or – 30 sec | less than 9 and a half minutes or more than 20 and a half min |
| Quality of Charts (presen-tations only) | Exceptio nal charts with no spelling errors, no more than 7 words per bullet, plus at least four excellent pictures and/or graphics that are clearly relevant and amplify the presentati on | Very good charts with no spelling errors, no more than 7 words per bullet, plus at least three pictures and/or graphics that are clearly relevant | Minimal misspelling and grammar errors but meaning is clear. Concise words, and no point with more than 7 words on a chart. At least two relevant pictures or graphics. | Minimal misspelling and grammar errors but meaning is clear. Concise words, and no point with more than 7 words. At least one relevant illustrations. | Minimal misspelling and grammar errors but meaning is clear. Concise words only. At least one illustration. | Multiple misspelling and grammar errors but meaning is clear. Words only. | Many misspellings and grammar errors. Hard to understand. Words only. |
| Quality of verbal presenta-tion (present-tions only) | Strong preparati on. Points flow well for each presenter and across presenter s. Excellent confidenc e. Is very persuasiv e | Strong preparation. Points flow well for each presenter and across presenters. Strong confidence. | Evidence of good preparation. Points flow well for each presenter but not across presenters. Good confidence. | Evidence of good preparation, but points do not flow well. Some confidence. | Some evidence of preparation. Some confidence. | Some evidence of preparation, but no confidence. | No evidence of preparation. Lack of confidence. |

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