Professional Engineering Perspectives On LLM Integration

David Hung

Abstract

This study investigates professional engineer's perspectives in their respective fields on the use of LLMs in their work. Semi-structured interviews were conducted to collect qualitative data on participants' opinions, experiences, and perspectives on LLM integration in their work. Interview transcripts were coded and analyzed through cross-case analysis to identify recurring themes and differences between participants. Findings suggest that engineers generally viewed LLMs positively, especially in the field of productivity gains through the automation of tedious tasks. Engineers from multiple fields reportedly used LLMs to improve communication efficiency through presentations and professional correspondence. All participants emphasized concerns regarding the reliability of using LLMs for professional work, stressing the importance of the use of a human to verify the AI outputs. A primary limitation of this study is its small sample size, which limits this study's generalizability to the entire field of engineering. Despite this, the study provides a basic understanding of the perspectives of professional engineers on LLM integration in engineering workflows.

Introduction

As artificial intelligence continues to develop throughout the twenty-first century, advanced AI models have become integrated to a greater extent in people's lives in multiple ways. As a result, applications can be found in both daily life and in jobs regarding data analysis or finance. (Hunter et al., 2018) Additionally, artificial intelligence has simultaneously become more capable in terms of intelligence and more accessible thanks to improvements in energy efficiency and reduced hardware costs. (Stanford, 2025) However, the integration of these models in the field of engineering may be more complex than in business or finance applications. The complexity of an engineer's work is generally considered beyond the capabilities of artificial intelligence, but recent advancements in AI technology may have reduced this gap.

According to IBM, The term artificial intelligence (AI) can be generally defined as technology that enables computers to simulate human intelligence in aspects like comprehension, creativity, and problem solving. (Stryker & Kavlakoglu, 2024) Machine learning was the very first form of artificial intelligence, and through the usage of algorithms, it can easily adapt its structure to solve different problems according to different datasets. More famously, the "neural network" learning method is a form of machine learning that is modeled similarly to the structure of the human brain where layers of information nodes interact to understand large or complex datasets. (Stryker & Kavlakoglu, 2024) The primary focus of the study is based on Generative AI (Gen AI) which can be found in models like Chat-GPT. Generative AI in itself is a model that has much greater capabilities than standard machine learning algorithms, being able to produce more complex responses to detailed prompts by comparing the prompt to its recorded data and responding with a similar result to the data. (Stryker & Kavlakoglu, 2024) The most common usage of Gen AI is found in Large Language Models (LLM), neural networks that are trained on large amounts of data, making them extremely versatile. These models are applicable to various issues such as code debugging, drafting legal clauses, and interpreting text. (Stryker, 2023) When mentioning Generative AI, household names like ChatGPT and Gemini come to mind. These AI models have gone beyond the capabilities of regular text processing, becoming Multimodal Language Models, which now allow them to generate images, audios, and more. (Varughese, 2025) These MLLMs are primarily used in modern applications, because of their larger application suite that is adaptable to different businesses.

Literature Review

In the body of knowledge surrounding AI usage in engineering, there are few studies on the explicit relationship between the two. However, similar studies help to contextualize the few studies that do exist, such as those related to the surrounding businesses or specific impacts on computer science. Reflecting the impacts of AI in businesses, a cross-case industry case study completed by Metzler et al. (2021) explores how artificial intelligence has affected leading companies in different markets, specifically their business model innovation (BMI). The findings of the study show that AI's development has altered company business models and strategies, resulting in the hiring of employees with AI skills, investing in AI research, updating infrastructure to support this new AI, making new partnerships, and more. AI is also seen in applications such as automation, predictive marketing, and customer service (chatbots). With the majority of companies making these changes, engineering companies would likely make the necessary alterations to their business models to remain competitive and attractive to investors. Additionally, by shifting their investments towards the development of AI, engineering companies would be inclined to incorporate AI into similar tasks like automation and communication to improve their efficiency.

In the field of computer science, artificial intelligence has continued to be applied to the work of developers, with studies by Houck et al. (2025) and Peng et al. (2023) exploring these impacts and changes to the computer science field. In the study conducted by Peng et al. (2023), the impacts of Github Copilot on code development speed were analyzed. Github Copilot is an integrated AI pair programmer that is intended to aid programmers in their tasks by suggesting code, finishing scripts, and providing feedback. When the group that used Github Copilot completed the task of writing an HTTP server in JavaScript, they did so with up to a 55.8% reduction in task completion time when compared to the control group. This shows the implications of AI in computer science, as productivity was shown to be improved drastically with the aid of Github Copilot. Building off of this study, the study completed by Houck et al. (2025) set out to determine how AI tools in general are affecting developers, not just Github Copilot. Using a survey to gather responses from developers, it was found that 75% of developers regularly used AI to complete tasks, with 90% of them reporting increases in productivity. Despite other limitations of AI such as task complexity, developer skill, and familiarity with AI, AI has generally proved to provide a strategic increase in productivity for developers in both individual and team settings.

The limited studies that are available on the impacts of artificial intelligence on engineering included Edgecomb et al. (2025) and Palazzo et al. (2026), in which the applications of AI in different disciplines and the perspectives of these engineers were explored respectively. According to Palazzo et al. (2026), the applications of artificial intelligence were explored throughout a variety of engineering disciplines, such as predictive maintenance in mechanical engineering, electrical optimization in electrical engineering, and traffic optimization in civil engineering. Additionally, Palazzo discusses the existing trends of AI application through design optimization or automation, as well as the future challenges AI needs to address, such as data training and ethical considerations. The study conducted by Edgecomb et al. (2025) provides another perspective in combination with Palazzo's establishment of the current integrations and applications of AI in engineering. This study gauges the current perceptions of engineers of different fields, through interviews that show that these engineers have similar and different outlooks for AI in engineering. The participants in the study agreed that AI will overcome possible barriers and become more integrated in engineering, along with other outlooks such as the automation of tedious tasks, but had the shared limitation that not much knowledge about functionality or existing tools restricted their vision of AI being integrated into their field. Together, the studies conducted by Palazzo et al. (2026) and Edgecomb et al. (2025) provide a view into how AI is affecting engineering and how the engineers in the field are perceiving and experiencing these changes.

Research Gap

In the existing research, there is a distinct lack of qualitative analysis on the perspectives of the engineers affected by AI. While there are articles on statistical impacts on productivity or qualitative studies on the usage in professional settings, analysis of engineering perspectives towards the impacts of LLMs has yet to be studied. These qualitative perspectives would help to contextualize existing quantitative research regarding AI integration and application in other studies, providing the stories and backgrounds that influence the data points behind the scenes. My research attempts to expand this area of study with interviews with professional engineers regarding the impacts of AI in their workflows and professional life, in order to gain a better understanding of engineering perspectives on the impacts of AI as it develops.

Methods

In engineering, there is an abundance of quantitative research done to match the statistical and quantitative manner of the discipline itself. Despite this, the usage of qualitative research has seen growth in the engineering field through pure qualitative studies as well as mixed methods research to gain a better understanding of issues like the meaning behind results. While quantitative research excels in explaining causes and correlation, qualitative research can help to reveal the perspectives and experiences behind the data points of a quantitative study, helping to provide a better understanding of the problem or cause in general. Specifically for artificial intelligence, there is likewise plenty of quantitative research regarding the job market and the productivity benefits of AI, but there exists a lack of qualitative research regarding how engineering specifically is impacted by AI. Articles about this topic are few and far between, most of which are not focused on the perspectives on AI by professional engineers, which is a critical aspect that must be considered in order to understand the context of how AI is impacting these engineers and their fields as a whole.

In combination with quantitative data on AI integration, qualitative studies that explore this aspect can serve to improve our understanding of the implications of AI for current and future engineers. As such, to answer the question "How do engineers perceive the impacts of Large Language Models on their professional engineering workflows?", a qualitative study spanning multiple disciplines must be conducted to understand the perceptions of these engineers and their experiences with LLMs.

Data Collection

In this study, semi-structured interviews were conducted to collect data from interviewees. Semi-structured interviews are a type of interview that enables researchers to gather more in-depth data and information than a regular interview by flexing interview questions around a framework of themes. (Mashuri et al., 2022) This framework serves as a guide for the interviewer to remain focused on the overall focus of the study while allowing for flexibility through “probing” questions that go beyond the general framework detail. Semi-structured interviews best fit the research that this study is attempting to conduct because it is able to be flexed around the interviewee’s responses to obtain more detailed or other relevant information. Additionally, this instrument was used in a similar study conducted by Edgecomb et al. (2025), who used semi-structured interviews to obtain qualitative data on AI perspectives.

These semi structured interviews were conducted over video conferencing systems like Zoom, Google Meets, and Microsoft Teams at a time most convenient for the interviewee. According to a study by Gray et al. (2020), video conferencing systems like Zoom provide researchers with a cheap and convenient alternative to face to face interviews. Furthermore, the study found that Zoom provided unparalleled convenience and accessibility, while also making meetings more accessible without the need to travel. With this improved accessibility, professional engineers could more easily meet online, improving the success rate of securing interviews and providing more time to discuss the topic in more detail. The interviewees consisted of professional engineers located in the Western United States, with or without a Professional Engineering certification. The approximately one hour meetings were recorded using OBS and transcribed using Descript; however, the transcription was manually checked for accuracy. Preliminary questions before the main interview consisted of questions regarding the interviewee's line of work, experience, and other non-identifying contextual information that was used to build a case for each interview. The questions asked inquired about the interviewee's observations, expectations, and perceptions on the integration of Large Language Models in their work and discipline as a whole. [Appendix A] During the interviews, the term AI was often substituted for Large Language Models referring to models like ChatGPT and Gemini, as a form of abbreviation despite being technically incorrect.

Analysis

Each case created from these interviews was compared against each other in a cross case analysis based on the information provided at the beginning of each interview. A case includes contextualizing information such as the field of engineering, years of experience in the field, location, and time, which helps to set the perspectives in their proper research contexts. For example, perspectives on artificial intelligence may change significantly between 2026 to 2030 or beyond. A cross case analysis is a method of pattern analysis that juxtaposes cases in order to observe similarities and differences between the cases, which assists the researcher in understanding the different facets of a topic and helps them to find patterns and relationships. (Khan & VanWynsberghe, 2008) To complete a cross case analysis of this study, transcriptions were first observed and important items/ideas were noted in a process known as coding. After categorizing the raw qualitative interviews into usable ideas/labels, the interviews were then organized in a table to reflect any similarities, differences, and outliers between the cases. With the inclusion of different perceptions in a cross case analysis, the results were documented in variations of perspective on the different common codes, instead of yes or no answers in order to better analyze the trends in the backgrounds and experiences of the interviewees.

Cross case analysis fits the purpose of the research well because of its relatively concrete results that it outputs as a result of the study. Because cross case analysis includes the collection of data from multiple cases, it is also able to provide a more comprehensive view of the existing opinions/perspectives that exist. This approach was chosen over a thematic analysis, because thematic analysis does not analyze the contexts of the interview outcomes. According to Ahmed et al. (2025), thematic analysis instead excels in identifying patterns and themes across an overall set of data, not individual cases. With the study focusing on the perspectives between different engineering disciplines, cross case analysis was best suited for the role.

Participants and Assumptions

In this study, the interviewees were engineers with professional work experience, located in the Western United States. The interviewees were all above the age of 21, and were asked to sign a consent form [Appendix B] that laid out the research plan, purpose, procedures, risk, and privacy information. Engineers with professional experience were chosen instead of engineers with the Professional Engineering (PE) certification as the inclusion criteria, because PE certification is only required for jobs related to public infrastructure, which would limit my dataset unnecessarily. However, this selection also assumes that these engineers have experienced or witnessed changes with LLM integration in their discipline. These engineers were asked to participate through referrals from educators in STEM fields, in a weak form of gatekeeper-assisted sampling.

Findings

Within Case Analysis

1. *Communication* - This code was assigned when an engineer referenced usage of LLMs for professional communication or presentation. Examples of LLM being used in communication include, “Gemini knows how I like to write emails and it’ll finish writing paragraphs for me.” and “They’ll (other engineers) use AI, specifically LLMS, to generate more concise PowerPoint presentation bullets.”
2. *Data Processing* - This code was assigned when an engineer referenced the usage of LLMs for processing data in large quantities, or when referencing LLM utilization to search for information within large data sets. Examples of data processing include, “It (LLMs) might be able to answer code questions or help; the building codes are publicly available, so it's able to skim through those and kind of provide input.”
3. *Coding Impact* - This code was assigned when an engineer referenced the impact of LLMs on coding or computer science. This information was not always first-hand, often heard from a friend. Examples of references to coding impact include, “I have some friends that are programmers [...] and a lot of them have basically said that it's reduced their eight hour work day to two hours.”
4. *Productivity* - This code was assigned when an engineer referenced effects of LLM integration on productivity, mostly from the perspective of time spent working. These

changes were consistently positive across the board. Examples of productivity impacts include, “That right there saves probably 40, 50 hours of labor” or “But overall it is really increasing 50% to 60%, drastically, drastically improving the productivity”

5. *Usage Type* - This code was assigned when an engineer referenced their perspective on the methods of utilization of LLMs, in terms of how they treat the LLM in their work. Examples of usage types include, “So for them (experienced engineers) it is a relief; you get a coworker, or an assistant.” and “You know, it's a much more complex calculator [...] but it's still just a tool.”
6. *Reaction to Integration* - This code was assigned when an engineer referenced their reaction or perspective on the integration of LLMs in their work, or their outlook on LLMs for the future. Examples of reactions to LLM integration include, “They're (other engineers) excited to learn the tool because it'll be help them […]”
7. *Inaccuracies* - This code was assigned when an engineer referenced the issues with reliability that is prevalent with LLMs, often accompanied by the common method of dealing with the issue. Examples of recognition of inaccuracies include, “It (LLMs) is really good for getting you 60% of the way, 70% of the way but the key is to not trust it.”

Each individual case followed the general structure of: *Years of Engineering Experience, Job Summary, Location,* and *Time.* It should be noted that when interviewing Participant A and B, the Windows built-in screen recording software was used. However, this proved to be a mistake, as both the recordings for Participant A and B became corrupted and therefore unintelligible. Despite this, meeting notes were substituted for Participant A and B’s responses in order to maintain discipline diversity and maximize the data obtained from the 5 interviews performed.

Participant Information

Participant A

Participant A is a Materials Science Engineer with 15 years of experience from the Western United States working with alloys. They gave an example of the practical usage of Gemini in their workflow primarily for inspiration, quick research, and reading research papers, mentioning the possibility to cut down task lengths drastically (1 hour to 20 seconds). Participant A stated that as AI usage improves in the future, materials would also advance significantly thanks to the ability of LLMs or similar models to quickly prototype and test experiments that would be costly or time consuming otherwise. Possible drawbacks mentioned included the lack of available information that LLMs can be trained on to pursue the task of recreating lab experiments, as most published results may not include methods to reach the final result. Possible concerns mentioned for the integration of LLMs in their work include the issue of reliability of LLMs, stating that they expect to see litigation and audits for LLMs in engineering in the future to ensure safety and certification. Participant A stated that their workflow has been positively streamlined with the help of LLMs, both through communication and finding credible information within credible sources.

Participant B

Participant B is a Civil Engineer (PE) from the Western United States with 9 years of experience working with organization, permit handling, and certification. They stated that LLMs can be practical, with applications in smaller parts of projects such as failure testing, communication, and programming, and can also be used to teach softwares like AutoCAD to engineers. Participant B expects to see AI develop into independent LLMs with specific uses, instead of all-rounders, and also stated that currently LLMs have helped significantly in cutting down work time when writing reports or organizing data. Participant B mentioned possible concerns about LLMs in the future, such as the need for human verification and interpretation, or the issue of reliability even with simple, irreplaceable tasks. Participant B also mentioned the possibility of utilizing LLMs professionally with proprietary data to create a searchable database of data like site samples or information that would be beneficial to the professional workflow.

Participant C

Participant C is an Electrical Engineer from the Western United States with 15 years of experience in building electrical systems, working primarily in management and system design. Participant C stated that LLMs can be practical given that it is trained on enough "non-googlable" data, with the benefits of being able to retrieve building code information and being able to help companies "do more with less people". Participant C stated that LLMs could potentially improve their effectiveness through more specialization and training on job-specific data, and cited existing implementation in communication streamlining through Microsoft . Possible concerns with the integration of LLMs included using proprietary data to train an LLM, along with the possibility of getting required certification where needed. Verification of products still needs to be done with a stamp, as Participant C states.

"I still have to put my stamp on the drawings, which is then certifying that I've reviewed everything. It's all been done under my charge."

Participant C also mentioned that LLMs are folded into the engineering workflow, still needing humans to iterate the LLM, and the significant time savings that LLMs can provide for their work,

“If we do a lot of government work, I've given it like a thousand pages of documents and summarized it into 10 pages, for example. That right there saves probably 40, 50 hours of labor, you know, of going through it.”

Participant D

Participant D is an Electrical/Mechanical engineer from the Western United States with 7 years of experience in Electrical Power Engineering, working with power grid system protection. Participant D stated that the practicality of AI integration is dependent on the use case scenario, with LLMs being extremely useful for finding information, reading textbooks, programming, or searching data. Participant D expects LLMs or alternative AIs to possibly develop as additions to softwares like Computer Aided Design softwares to better streamline workflows, with the most concerns about LLMs being their lack of reliability and their ability to solve moral dilemmas. Participant D stated,

“Even if it's like 95% good(accurate) for AI doing simple math, there's a lot of simple math in my job. It's not good enough. You have to have it basically be 100% .(accuracy)”.

Aside from the concerns, Participant D stated that LLMs have helped in communication and in engineering workflows (if the engineer knows how to utilize it effectively) but it is not primarily used for engineering for their job.

Participant E

Participant E is a Software Engineer from the Western United States with 30 years of experience as a backend Java developer. Participant E has seen major usage of LLMs like ChatGPT and Gemini in the programming field, with productivity being significantly multiplied. LLMs have been integrated to the extent stated by Participant E to which,

" It's (LLMs) not like basic documentation or good helpers/agents anymore, we are looking at it more as coworkers."

Possible concerns with LLMs being integrated into software engineering include the issue of integrating it into the actual programming, as it is more difficult to monitor the AI for validity and because of its lack of accuracy. Instead, Participant E states that integration in sales and marketing is easier and more effective for the company. Participant E has also cited multiple benefits in the workflow (that scale with experience) such as benefits in productivity, prototyping ability, and other systems.

Table 1 - Codes Applied To Interviews

	Participant A (Materials Science)	**Participant B (Civil Engineering)**	**Participant C (Electrical Engineering)**	**Participant D (Electrical Engineering)**	**Participant E (Software Engineering)**
Communication	HR usage in their emails	Personal use for emails/reports	Personal usage for helping to write emails	Used personally for emails/ resumes	Extensively used in marketing emails/texts
Data processing/ analysis	Read Google Scholar articles +	Reads large datasets and reports + Potentially	Retrieve construction codes + Effective	Search for information, read textbooks +	Automatically creates code documentation

	Facility Capability search	writing reports	data processor	Good for data searching	
Productivity	Depends, 1 hour of work → 20 seconds	Depends, Saves time as a jumping off point	Depends, Potentially ~50 hours saved	Skips the tedious steps, makes things more efficient	Depends on experience, Day's work → 1 hour
Usage Type	Productivity tool, coworker/ consultant	Productivity tool, low level assistant, coder	Data searcher, communicati on manager	Mostly accurate source, CAD, addon for productivity	Coworker, frontend assistant for the backend and vice versa
Inaccuracies	Experiences errors occasionally, comparison to real knowledge + Should be checked by human engineers	Unreliable even for simple tasks like soil sampling + Needs human verification and interpretation	Experiences confident errors + Needs human verification	Not 100% accurate → cannot be fully trusted + AI needs to be 100% accurate to be useful	Lack of accuracy is present and requires validation + Difficult to address, monitoring on a large scale
Reaction to Integration	Positive (If responsibly used and results are verified)	Neutral (Believes AI is inevitable and capable)	Positive (AI potential may be limited in engineering)	Positive (Can help in certain instances, still much to develop)	Positive (Some fear of future replacement)
Coding Impact	Can help non-coders create programs easily	Used to code programs without coding experience	Knows programmers who have had significant productivity improvement s	Programming is mostly accurate and can be used "out of the box"	Significantly impacted + Will not fully replace coders but can potentially

Results of Cross Case Analysis

For each engineer, the codes were applied to the interviews and their respective perspectives and experiences (see Table 1). One item to note is that when attempting to answer the research questions, engineers would respond based on the tangible benefits or drawbacks of LLMs, which resulted in a more result-based outcome of the study. As a result of the analysis, the following themes emerged:

1. *Productivity benefits with LLMs are field/task dependent*

Productivity gain was one of the main themes found in all five cases of engineers in the study, with Participants A, B, C, D, and E all citing some form of productivity improvement with the integration of LLMs in their work. All participants, when describing their benefits with productivity, quantified the improvement based on time spent working, dependent on the type of work being streamlined. For example, Participant C estimated major time savings for specific parts of the job that were the most tedious.

“If we do a lot of government work, for example, I've given it like a thousand pages of documents and summarized it into 10 pages. That right there saves probably 40, 50 hours of labor, you know, of going through it.”

Such significant benefits were contrasted with benefits from other participants like Participant A, who estimated an hour’s worth of time saving. This time saved was primarily dependent on how much data processing that LLMs could take over in the participant’s workflow, with jobs with more data processing receiving more time-saving benefits than others. The trend shown in the data showed that it was not only the tasks that caused the dependency in productivity, but also the disciplines that had more or less work that was able to be automated by LLMs. For example, Participant A cited less time saving than Participant E, hailing from materials science engineering and software engineering respectively, likely due to the difference in automatable work that they work with. This overwhelmingly present theme of improved efficiency in engineering work and reduced working time for certain tasks is representative of the trend found in Peng et al., 2023, implying that the trend of increased productivity could be applicable to other industries as well.

2. *LLMs are consistently integrated in professional communication*

The usage of LLMs for different forms of communication was also a major theme found in all cases, in which engineers either personally utilized or experienced their workplace utilizing LLMs to a greater extent for communication. Participants A, B, C, D, and E all mentioned some form of LLM utilization in their work, with some citing different methods of integration. Participant E referenced the usage of LLMs for call centers from the sales perspective, stating that LLMs could help to take the first level of calls similar to the functionality of a call center, then forwarding the possible sales to the real people. Participant A, B, C, and D all referenced usage of LLMs for the purpose of streamlining emails and basic, low-level administrative tasks, but Participant D mentioned a uniquely important aspect to the increased usage of LLMs in communication in the field of engineering.

“Engineers are typically on average going to be very socially awkward and not good at talking and being concise so for their presentation skills, basically they're supplementing their lack of social ability in the form of writing emails in a way that is nicer to read [...], making PowerPoint presentations more natural, or just finding something to write on their PowerPoint slide.”

Participant D’s reference to the social awkwardness of engineers, even in the professional world, brings up an interesting point about the significance of the integration of LLMs in engineering, which is supported by the 11 Academia Networks Team (2020). In this blog, it is also stated that a common misconception about engineers is that they have no social skills and have poor communication skills. With LLMs now being able to support engineers’ communication skills, the field of engineering as a whole could either develop a dependency on LLMs to communicate effectively, or potentially become even more efficient with the help of LLM communication. This could imply a future of reliance on LLMs for communication for engineers, as the engineering field could communicate results and information more clearly and efficiently, reducing miscommunication and improving understanding between engineers and non-engineers.

3. *LLM developed results must be verified by human engineers*

The importance of verification of results coming from LLMs was the primary theme emphasized across all cases, with all participants citing some form of inaccuracy resulting from using LLMs for information. Participants A, B, C, D, and E all personally experienced the lack of reliability of LLMs, and expressed their different methods of verifying or checking the results that are output from LLMs. Participant A first stated that they often compared their knowledge that they learned from their college education with the information presented by the LLMs as a form of verification, while Participant B stated that they wouldn’t trust LLMs for even simple tasks, and recommended human verification and interpretation of outputs. Participant C’s experiences with unreliable LLM information led to a resolution of assigning LLM to low risk, easily reviewable tasks. Participant D simply recommended not trusting LLM outputs and double checking them, and Participant E recommended applying LLMs to easier, lower risk areas like sales and marketing. While the levels of trust varied between engineer and discipline, having a human verify the results of LLMs remained the easiest and most agreed upon method of resolving these inaccuracies. Participants A, B, C, D, and E all conducted or recommended human verification or “stamp” on the outputs. An interesting input from Participant C was the idea that humans will always be a constant in the AI equation, at least in engineering.

“Somewhere in this process, it's always going to end up being a human, unless overall society shifts to trust machines. Because it's always the human checking what the AI has done.”

This idea has been agreed upon by the other cases in the study, and could imply that this would apply for the future of engineering. In the future, when AI becomes more advanced, humans could very well be still in charge of verification, double checking, and inputting the data, at least until AI improves its accuracy.

Limitations

Before discussing the conclusions of the study, the limitations must be addressed in order to clarify the study. Limitations of this study include, but are not limited to, sample size, researcher experience, and human error. The sample size was the most challenging component as a high school student, as finding professional engineers who would take the time to meet with me for an hour proved to be challenging. While it was attempted to obtain engineers from all different fields, a duplicate field of electrical engineering could make the study slightly skewed in the perspective of electrical engineers, instead of the interdisciplinary approach that was originally planned. Additionally, a sample size of only one engineer per field may not be generalizable to the entire population of engineers in this field. Researcher experience limited some of the accuracy of the study, as my inexperience in research procedure led to the loss of recordings and transcriptions for two of the interviews, which could make some of the perspectives of the two engineers slightly different from what they originally stated. Lastly, human error in remembering the interviews and the translation between transcription to codes could have slightly skewed the results subconsciously.

New Understandings

To understand the answer to the question, "how do engineers perceive the impacts of Large Language Models on their professional engineering workflows?", the results of this study must be applied to the real world. This study contributes to the understanding that professional engineers have generally positive perspectives or experiences with the integration of LLMs in their work, with improved productivity and communication at the risk of LLM inaccuracy. Additionally, a potential reason for reliance on LLMs for communication was found in the study, suggesting that engineers may be subject to a reliance on LLMs to make up for poor communication skills. This is potentially a double edged sword, in that it could either help engineers overcome their possible social issues to communicate their results more effectively, but simultaneously it may result in an overreliance on LLMs, deprecating engineers' social skills outside the digital world instead. Additionally, this study's results suggest that the studies done by (Houck et al., 2025) and (Peng et al., 2023) may be applicable to other engineering disciplines, as productivity benefits were seen both inside and outside computer science disciplines. Engineers across the different disciplines are likely to experience varied benefits in productivity with the added integration of LLMs in their workflow, but this is highly dependent on the tasks being completed and the discipline's potential for streamlining with AI.

Future research in this area could include research into the statistical improvements that LLMs have provided for engineers not in the software engineering field. Because the surrounding literature seems to have a large gap in the findings on LLM impacts on traditional engineering disciplines, quantitative research could help solidify findings in qualitative research such as that found in this study. Along with the statistical evidence of LLM improvements, there could also be research done more in-depth on the actual amount of perceived workload that is relieved from engineers with the help of LLMs, possibly even with engineering students.

References

11 Academia Networks Team. (2020, December 7). *The 10 Most Common Misconceptions About Engineers*. NewEngineer.com. https://newengineer.com/blog/the-10-most-common-misconceptions-about-engineers-948663

Ahmed, S. K., Mohammed, R. A., Nashwan, A. J., Ibrahim, R. H., Abdalla, A. Q., Ameen, B. M. M., & Khidhir, R. M. (2025). Using Thematic Analysis in Qualitative Research. *Journal of Medicine, Surgery, and Public Health*, *6*(6), 100198. ScienceDirect. https://doi.org/10.1016/j.glmedi.2025.100198

Edgecomb, I. M., Brisco, R., Gunn, K., & Holliman, A. F. (2025). Artificial Intelligence in engineering design: an industry perspective. *Proceedings of the Design Society*, *5*, 641–650. https://doi.org/10.1017/pds.2025.10078

Gray, L., Wong-Wylie, G., Rempel, G., & Cook, K. (2020). Expanding qualitative research interviewing strategies: Zoom video communications. *The Qualitative Report*, *25*(5), 1292–1301. https://doi.org/10.46743/2160-3715/2020.4212

Houck, B., Lowdermilk, T., Beyer, C., Clarke, S., & Hanrahan, B. (2025, July 31). *The SPACE of AI: Real-World Lessons on AI's Impact on Developers*. ArXiv. https://arxiv.org/pdf/2508.00178

Khan, S., & VanWynsberghe, R. (2008). Cultivating the Under-Mined: Cross-Case Analysis as Knowledge Mobilization. *Forum Qualitative Sozialforschung / Forum: Qualitative Social Research*, *9*(1). https://doi.org/10.17169/fqs-9.1.334

Mashuri, S., Sarib, M., Rasak, A., Alhabsyi, F., & Ruslin, R. (2022). Semi-structured interview: A methodological reflection on the development of a qualitative research instrument in educational studies ruslin. *IOSR Journal of Research & Method in Education*, *12*(1), 22–29. https://doi.org/10.9790/7388-1201052229

Metzler, D., Neuss, N., & Muntermann, J. (2021). Artificial Intelligence and Business Model Innovation in Incumbent Firms. *Die Unternehmung*, *75*(3).

Palazzo, S., Palazzo, F., & Zambetta, G. (2026). *View of The Role of Artificial Intelligence in Advanced Engineering: Current Trends and Future Prospects*. Ukscip.com. https://ojs.ukscip.com/index.php/jic/article/view/959/768

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). *The Impact of AI on Developer Productivity: Evidence from GitHub Copilot*. https://arxiv.org/pdf/2302.06590

Stanford University. (2025). *The 2025 AI Index Report*. Stanford.edu. https://hai.stanford.edu/ai-index/2025-ai-index-report

Stryker, C. (2023, November 2). *What are large language models (LLMs)?* Ibm.com; IBM. https://www.ibm.com/think/topics/large-language-models

Stryker, C., & Kavlakoglu, E. (2024, August 9). *What is artificial intelligence (AI)?* IBM. https://www.ibm.com/think/topics/artificial-intelligence

Varughese, J. (2025, July 30). *Multimodal LLM*. Ibm.com. https://www.ibm.com/think/topics/multimodal-llm

APPENDICES

Appendix A - Questions asked during the semi-structured interviews

1. How long have you been a professional engineer for?
2. What field of engineering do you work in?
3. How many years of experience do you have in this field?
4. What is a summary of your role in your job?
5. How practical do you think LLMs are for the discipline of engineering?
6. How do you think engineers will deal with the issue of reliability in LLM information?
7. What alternatives for LLMs, if any, would be better suited for assisting engineers?
8. How do you think LLMs will impact engineering as a whole?
9. In your experience, how have LLMs been integrated in your field of engineering?
10. Do you utilize LLMs in your professional engineering workflow?
11. Would you say that you have seen an increase in the usage of LLMs in your company?
12. If your company were to further integrate LLMs into the company workflow for things like meetings, writing documents, and creative projects, how would you react?
13. How integrated would you say LLMs have become in your field of engineering relative to other disciplines?

Appendix B - Adult Consent Form

Informed Consent to Participate in Research
Information to Consider Before Taking Part in this Research Study

You are being asked to take part in a research study. Research studies include only people who choose to take part. This document is called an informed consent form. Please read this information carefully and take your time making your decision. Ask the researchers or study staff to discuss this consent form with you, please ask him/her to explain any words or information you do not clearly understand. We encourage you to talk with your family and friends before you decide to take part in this research study. The nature of the study, risks, inconveniences, discomforts, and other important information about the study are listed below.
We are asking you to take part in a research study called: Professional Perspectives On AI Integration in Engineering.
The people who are in charge of this research study are XXXXX.

The research will be conducted through online conferencing/video calls.

Purpose of the study
The purpose of this study is to explore professional perspectives on the integration of artificial intelligence in the workflow of engineers in the US through models like ChatGPT or DALL-E in multiple fields of engineering in 2025.
Study Procedures
If you take part in this study, you will be participating in one-on-one interviews through an online conferencing platform and answering topic related questions. The interview will be recorded, transcribed, and analyzed.
Total Number of Participants
5-10 participants
Alternatives
You do not have to participate in this research study.
Benefits
The results of the study will be sent to you after completion.
Risks or Discomfort
This research is considered to be minimal risk. That means that the risks associated with this study are the same as what you face every day.
Compensation
You will receive no payment or other compensation for taking part in this study.
What will it cost you to take part in this study?
It will not cost you anything to take part in the study
Privacy and Confidentiality

We will keep your study records private and confidential. Certain people may need to see your study records. By law, anyone who looks at your records must keep them completely confidential. The only people who will be allowed to see these records are:
The research team, including the Principal Investigator, study coordinator, research nurses, and all other research staff.
Certain government and university people who need to know more about the study. For example, individuals who provide oversight on this study may need to look at your records. This is done to make sure that we are doing the study in the right way. They also need to make sure that we are protecting your rights and your safety.
Any agency of the federal, state, or local government that regulates this research. This includes the Department of Health and Human Services (DHHS) and the Office for Human Research Protection (OHRP).
The USF Institutional Review Board (IRB) and its related staff who have oversight responsibilities for this study, staff in the USF Office of Research and Innovation, USF Division of Research Integrity and Compliance, and other USF offices who oversee this research.
We may publish what we learn from this study. If we do, we will not include your name. We will not publish anything that would let people know who you are.
Voluntary Participation / Withdrawal
You should only take part in this study if you want to volunteer. You should not feel that there is any pressure to take part in the study. You are free to participate in this research or withdraw at any time. There will be no penalty or loss of benefits you are entitled to receive if you stop taking part in this study. Decision to participate or not to participate will not affect your job status.
New information about the study
During the course of this study, we may find more information that could be important to you. This includes information that, once learned, might cause you to change your mind about being in the study. We will notify you as soon as possible if such information becomes available.
You can get the answers to your questions, concerns, or complaints
If you have any questions, concerns or complaints about this study, contact X at XXXXXXXXX
If you have questions about your rights as a participant in this study, general questions, or have complaints, concerns or issues you want to discuss with someone outside the research, call XXX, at XXXX or email at XXXXXXXX

Consent to Take Part in this Research Study
It is up to you to decide whether you want to take part in this study. If you want to take part, please sign the form, if the following statements are true.
I freely give my consent to take part in this study and authorize that the information as agreed above, be collected/disclosed in this study. I understand that by signing this form I am agreeing to take part in research. I have received a copy of this form to take with me.

Signature of Person Taking Part in Study Date

Printed Name of Person Taking Part in Study

Statement of Person Obtaining Informed Consent (THIS IS THE RESEARCHER)
I have carefully explained to the person taking part in the study what he or she can expect from their participation. I hereby certify that when this person signs this form, to the best of my knowledge, he/ she understands:
What the study is about;
What procedures/interventions/investigational drugs or devices will be used;
What the potential benefits might be; and
What the known risks might be.

I can confirm that this research subject speaks the language that was used to explain this research and is receiving an informed consent form in the appropriate language. Additionally, this subject reads well enough to understand this document or, if not, this person is able to hear and understand when the form is read to him or her. This subject does not have a medical/psychological problem that would compromise comprehension and therefore makes it hard to understand what is being explained and can, therefore, give legally effective informed consent. This subject is not under any type of anesthesia or analgesic that may cloud their judgment or make it hard to understand what is being explained and, therefore, can be considered competent to give informed consent.

Signature of Person Obtaining Informed Consent / Research Authorization Date

Printed Name of Person Obtaining Informed Consent / Research Authorization