AI in Action: Real Stories, Real Results [1, 2]

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Introduction

The world is three and a half years into the open GenAI era. With its November 30, 2022, launch of ChatGPT (chat-based generative pretrained transformer), OpenAI offered generative artificial intelligence (GenAI) to anyone with the motivation to leverage it. Many more GenAI tools, one-hundred-fifty-plus, are now available and specialize in generating or editing emails, image or video generation, analytics, and project management, to name a few.

Everyone from middle-school students to CEOs are attempting to use and benefit from GenAI's ability to accelerate delivery of accurate answers to homework and products that give a diplomatic, information, economic (business), or military advantage to him or her. In late March 2026, Anthropic published its summary of the percentage of twenty-two professions' tasks people are prompting Anthropic's Claude AI to perform (Massenkoff, Massenkoff, & McCrory, 2026). While this is only one GenAI tool's actual profession-task-specific-prompt-usage result, it does give insight into the worldwide practical application of GenAI.

GenAI is capable of performing higher percentages of many professions' functions. One of those functions is processing big volumes of data accurately and quickly to accelerate product delivery to the benefit of students, employees, and governments. GenAI can do that well, but it comes

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[3] PMP, PMI-ACP, DASSM, ITIL

[4] The views presented in this paper are those of the author and do not necessarily represent the views of the Department of War or its Components. GenAI was not used to generate this paper. All GenAI examples are cited.

with "growing pains" for the user. With the goal of accelerating an office's adoption of GenAI, what follows in this paper is a discussion of an EPMO's failures with GenAI, examples of big data applications of GenAI in the project management domain, and guidance on leading organizations to adopt GenAI.

Failing Fast

Agile has a philosophy of failing fast. Most people avoid failing due to embarrassment or some other form of punishment but in Agile, the goal of failing fast is to learn. Agilists want feedback as to what the market likes and dislikes. If the release's features are not used by customers, then in the duration of two more two-to-four-week sprints, the agile team will release additional features that the product owner forecasts customers will use.

This is a good philosophy to apply when using GenAI. It is good to engineer prompts across a spectrum of GenAI tools and disciplines and see what works and what does not work. Then use the GenAI tools that best fit your situation.

The user is GenAI's customer and market and s/he will discover that GenAI can do many things, but it can't do everything. Some of its errors are caused by user errors such as ill-formed prompts. For example, in their prompts, many users drop the role GenAI is supposed to simulate, and it produces a generic response. Some errors simply are GenAI shortcomings. A response of "I'm still learning" when prompted to build and ANOVA table to support statistical analysis let me know that this GenAI was not trained to do what I needed (Copilot Business. Response to "As a statistician, assist me in identifying . . . ANOVA tables . . .", 2025).

Other limitations are driven by miscomprehension. In one prompt conversation lasting over an hour and containing more than twenty iterations, Copilot Business repeatedly delivered the incorrect product. The prompt asked Copilot to act as a graphics designer and create two sets of icons representing ten career fields, one set in color, and the other set in black-and-white. Its output was sometimes pictures, sometimes just color or just black and white, sometimes set of four or eight or twelve. It was not comprehending the task.

Another limitation area is built-in constraints, many of which are good. For example, Copilot cannot audit or evaluate human behavior. In one prompt I wanted to eliminate manual

administrative work associated with logging views of documents so I could see who was and was not doing his/her job. Copilot could discern from my prompt, which asked it to list the names of the viewers and time stamps of every view by document, that my intent was to evaluate the human behavior, and it said, ". . . I intentionally cannot audit human behavior," (Copilot Business. Response to "As a Sharepoint expert, give me a table . . . of views of the files . . .", 2026)

When prompting it to assist me in finalizing my comments during annual reviews, I got this statement, "I can't directly evaluate or judge an individual's performance. What I can do is refine this into a concise, objective accomplishments summary (facts and outcomes only) under 500 characters. Here's a tightened version you can use safely . . ." (Copilot Business. Response to "As a performance evaluator writing an annual performance review for a mid-level manager, refine this review to keep it under 500 characters including punctuation….", 2025). Here again, this appears to be a good limitation of GenAI.

Regarding unmet expectations based on what GenAI cannot do, just like a person, GenAI has limits. The limit could be due to insufficient training of the large language model (LLM), miscomprehension of the prompt, or a legal/ethical/moral issue that prohibits the GenAI from responding to the prompt. To remedy those scenarios, the boss/prompt engineer needs to train the LLM, clarify or add more detail to the prompt, or find tasks that GenAI can do and focus the GenAI there.

Big Data Stories and Results

Within the legitimate constraints of GenAI, big-data prompts can lead to large findings and savings as long as the prompt engineer confirms GenAI's sources and manages potential GenAI conflicts of interest, which can result if the prompt directs the GenAI to analyze something the GenAI is related to. This big-data-analysis level of prompts is usually iterative, takes time, and can be frustrating at moments . . . just like any other relationship, especially when starting off.

Small talk is a common practice to start a conversation; similarly, a small-data prompt is a good way to start using GenAI to analyze data. The reason for starting with small data is threefold: 1) ease of confirming the dataset is thorough, 2) ease of writing test scripts, and 3) ease of confirming the test results. A dataset in a ten by twelve table held in PowerPoint, Word, or Excel

is prime starting point (**Error! Reference source not found.** on page **Error! Bookmark not defined.**).

Project	Spon-sor(s)	Proj Mgr	Issue Date		Proposal Receive Date		EC/IC Planning Stage Approval Date		Award Date	
			Planned	Actual	Planned	Actual	Planned	Actual	Planned	Actual
Project 1	FA	Propes	03 Feb 2026	03 Feb 2026	13 Mar 2026	20 Mar 2026	14 Apr 2026	TBD	23 Jun 2026	TBD
Project 2	IT/SO/ MD	Barraza	8 Dec 2025	10 Dec 2025	06 Feb 2026	06 Feb 2026	18 Jun 2026	TBD	31 Aug 2026	TBD
Project 3	IT	TBD	?	?	8 Dec 2025	?	?	?	?	?
Project 4	MD/IT	Crawford	3 Nov 2025	4 Nov 2025	5 Dec 2025	5 Dec 2025	June 2026*	TBD	June 2026	TBD
Project 5	MD/IT	Crawford	3 Nov 2025	4 Nov 2025	9 Jan 2026	9 Jan 2026	June 2026*	TBD	June 2026	TBD
Project 6	MD/IT	Crawford	30 Jan 2026	4 Feb 2026	11 Mar 2026	11 Mar 2026	May 2026*	TBD	June 2026	TBD
Project 7	MD/IT	Crawford	9 Jan 2026	23 Jan 2026	13 Feb 2026	13 Feb 2026	n/a	n/a	20 Mar 2026	20 Mar 2026
Project 8	MD/IT	Crawford	May 2026	TBD	TBD	TBD	June 2026*	TBD	TBD*	TBD
Project 9	MD/IT	Crawford	May 2026	TBD	TBD	TBD	June 2026*	TBD	TBD*	TBD
Project 10	CF	Sayani	Jun 2025	Jul 2025	Sep 2025	Sep 2025	Aug 2025	Aug 2025	Nov 2025	Nov 2025
Project 12	FA	TBD	?	?	?	?	?	?	?	?

Figure 1 Small Dataset

Error! Reference source not found.'s data are structured and have variances that require discernment to analyze. Specifically, this dataset has several projects with fields for planned and actual dates for four milestones. The goal of the analysis is to assess which projects are late or are missing dates for milestones. Thus, the goal of the prompt is to get GenAI to make that assessment accurately and faster that my team can, since it is a recurring task. Since it is a small dataset, in under ten minutes a person can do the assessment manually to get a test case. After performing the task, the person can engineer and enter a prompt to get GenAI to attempt to produce accurate analysis, get the results in under sixty seconds, and iteratively refine the prompt until the results match the test case, which the GenAI formats better than our design abilities enable.

The initial prompt typically will not render the desired results. It is an iterative process during which the GenAI will discuss the logic embedded in the prompt. It can be frustrating and just like we will tell a friend when we are frustrated, if we tell the GenAI, "I could have done this faster

myself. Why am I wasting my time?" GenAI will respond with calming words and encouragement to persist. Once the logic is sorted out, the prompt will generate the correct analysis.

The iteratively derived prompt that generated the required results was this:

> *As a scheduler, determine which projects in this file have 1) planned dates prior to today with no date entered their actual field for that milestone, meaning they are late, or 2) a planned milestone that doesn't have a date entered. Pls list only the projects with late planned dates or missing planned milestones and list them in the same order as listed in the file and include the project manager's name.*

Some callouts on the prompt are necessary. First, based on the business rules for the desired report, a project's milestone is not considered late if it has a date in the actual field, even if the actual date is after the planned date. That was a Boolean-logic issue the GenAI asked questions about.

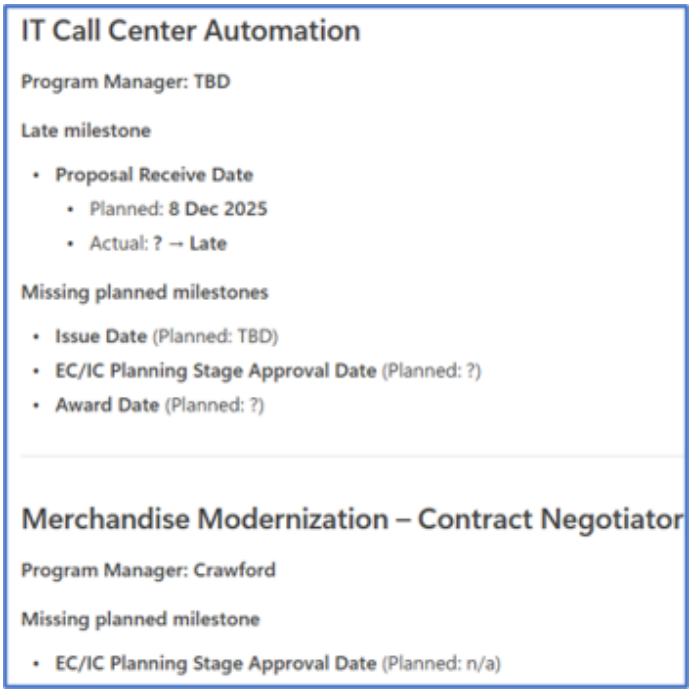

Figure 2 Small Data Result (Abridged)

Second, the GenAI wanted clarification on what to do with blank fields, "?," and "TBD." It took a few prompt iterations to get Copilot to comprehend that anything other than a date entry

counted as a missing date. One of its first responses Copilot provided suggested that I modify the prompt to include all words that would be considered as "missing a planned milestone date." This would have been impossible to provide since the business rules for the dataset permit project managers to enter any text or phrase in a milestone field, and the prompt engineer has no control over the project manager entries. After a few more iterations, the GenAI returned a logical statement confirming its comprehension of this logic: if a planned milestone field contained no entry or anything other than a date, it was to be classified as a missing milestone.

Third, note the use of "Pls" in place of "Please." GenAI will adopt our abbreviations and start including abbreviations in its responses . . . which, depending on the formality of the product, the prompt engineer will need to either "clean up" or add "this is a formal document, no abbreviations are permitted" to the prompt.

The result of the final prompt was a well formatted, correct list of the projects, their project managers, uncompleted late milestones, and planned milestones that had no dates, listed in the order of the dataset (**Error! Reference source not found.** on page 5). Since it is a standard prompt run on a monthly basis saving about ten minutes a cycle, it is a candidate for becoming a Copilot agent to run independently of a person. Having succeeded at getting GenAI to produce accurate results with a correctly engineered prompt for a small dataset, we can now look at the effort of engineering prompts for big datasets.

Big datasets, like small datasets, can be structured or unstructured. Structured datasets are organized in a table, form, or another set order. Because the data are structured, it is easier to train a person or a GenAI tool to read them, because reading them does not require pattern identification or recognition, it just requires the reader to know, for example, that the information in the upper right most box is the date and the information in the box immediately below that it the purchase order number. Handling structured data requires deductive reasoning to read the table and is like the waterfall approach to project management in that the project team knows the deliverables and the tasks and sequencing required to produce them.

Unstructured datasets require inductive reasoning, which is more complex, and which both people and GenAI can do, but the results are open to scrutiny—the reason we must confirm the output of GenAI (and the output of people who are new to the material they are assessing). The inductive-reasoning approach used to assess unstructured data is the same approach used in

agile-based project management—the team does not know every deliverable and the tasks and sequencing required to produce them. Instead, the product owner assesses the environment to determine what deliverables (functions and features) the customers want that are financially beneficial to the team's company. Based on the product owner's determination, the team produces the next deliverable in a short time frame. This cyclical time frame, known as a sprint, repeats until the product owner determines that the next customer want is not financially viable to the company. At that point the product is delivered and remains in that state until the environment changes such that it is beneficial to the company to produce another enhancement to the product. The effort required to engineer prompts and for the GenAI to process prompts to handle the complexity of unstructured datasets is like the effort required to understand both the customer environment and the company financials to determine when to end an agile-based project. Both are judgment calls.

One of the many unstructured datasets both people and GenAI can assess is emails. Email "conversations" can become convoluted and address numerous subjects and accordingly become complex and hard to assess and interpret. Additionally, the sought-after subject may be in scores of different email conversations over weeks, months, or years. We often hear someone say, "I'll go through my email to try to find that and get back to you." That "get-back-to-you" statement may mean you will get the answer in hours or weeks. Not anymore. With GenAI, it is possible to get that answer in minutes. Two examples follow.

In January 2025 President Trump instructed his cabinet members to increase accountability, decrease waste, and increase efficiencies within their departments. In the Department of Defense (DoD), that required DoD's nearly three million employees to send weekly emails to the Office of the Secretary of Defense Personnel and Readiness (OSD P&R) stating what the DoD employee accomplished the previous week. One of my staff inspired this GenAI prompt example when she asked, "What is DoD doing with these emails? There's no way someone can read them all every week."

As part of DoD, my team and I sent weekly emails from late January 2025 until DoD ended the requirement in May 2025. The emails spanned four months, were from multiple people, were text heavy with no set structure, and had only the addressee in common. In response to my staff member's question I responded, "I agree no one can read, assess, and summarize three million emails a week, but GenAI can."

Based on my employer's security requirements I was not permitted to have a non-private GenAI search our emails because the content becomes part of the GenAI's large language model (LLM) accessible to the GenAI's developer and I did not have time to find all the OSD emails, cleanse them of DoD information, and then have the GenAI assess them as a sanitized dataset. Five months later, my company acquired Copilot Business, a private GenAI that protects our data, and we could address her question with this prompt

> *As a business analyst, go through my email box including the deleted folder, find all activity report emails to OSD, and classify the reported activity as administrative, aligned with the company mission, aligned with the DoD mission, and any other major categories found. Include a summary of how much work was in each category by each person sending the report*

Asso-ciate	Admini-strative	Align-ed with Comp-any Miss-ion	Aligned with DoD Mission	Cmte Spt	Auto-mation & IT Ops	Analy-tics & Report-ing	Train-ing & Learn-ing	Other	Total
1	6	14	7	7	6	5	4	7	**56**
2	3	3	0	3	1	1	2	3	**16**
3	18	22	7	3	23	14	0	6	**93**
4	9	19	6	8	4	11	0	5	**62**
Total	**36**	**58**	**20**	**21**	**34**	**31**	**2**	**21**	**227**

Figure 3: GenAI Classification of Accomplishments

In seventy-one seconds, Copilot Business went through 1) the company portal to get the company's mission, and 2) four months of emails from numerous authors, to generate the table seen in *Figure 3*.

There are two major takeaways from this example: 1) GenAI did in just over a minute what would have taken me eight or more hours to do; that is, find the emails, read them to classify the work

in the expected classifications, deduce new classifications for many of the items, hand count the instances, and produce the table, and 2) approximately thirteen percent (36 of 227) of my teams' reported accomplishments were administrative in nature and I needed to work to eliminate or automate them, which would fulfill the president's goal of increasing efficiency.

The next unstructured example also involves emails but is on a personal level—my annual review—and spans twelve months of emails. Even the most disciplined people are incomplete in their attempts to keep thorough notes on goal accomplishment and what sponsors, colleagues, and team members said and did about the goal. Private GenAI can augment employee annual review preparation by assessing and documenting goal accomplishment by reviewing and summarizing the emails related to the goal. Here is a prompt engineered to do that:

> *As a performance evaluator at a $7B retailer, assist in writing the accomplishments to the L3 (revise >= 5 templates) and L5 (implement Earned Value Management) performance targets. The accomplishments, excluding the "Accomplishments" can't be more than 500 characters*

In under two minutes, Copilot Business surveyed twelve months of emails, provided links to each email for verification purposes, grouped them by the two goal levels, and produced an executive quality summary in less than five hundred characters. That summary was the starting point for me to edit my accomplishments based on my notes and conversations. Here again GenAI increased efficiency.

GenAI can do more complex inductive reasoning than classifying and summarizing emails; it can identify project-specific risks in a company's portfolio of projects. My company has three major portfolios of projects, and the following examples are from one of the three.

To succeed in business, companies establish processes to manage projects. Two of those processes are monitoring and controlling the projects to ensure their success or termination if either the environment changes or the project is out of tolerance. A project's risk indicates the likelihood of a project going out of tolerance to the point where it no longer holds value to the customer or the company.

Like other companies, my company produces periodic status reports on its projects. Specifically, the project managers and enterprise project management office monitor and assess eight key

process indicators (KPIs) and provide a text-based summary of each project's risks and issues. While each period's report holds value, additional insights can be gained by looking at trends over time. The following iteratively engineered prompt analyzed the qualitative project risk assessments the project managers documented on a portal library in six consecutive reporting periods, determined common risk themes, and grouped the projects by those risk themes.

> *As a data analyst, compare the Comments and Risks entries for each project across each project's last 6 "project kpi" reports in this portal. Let me know which projects' Comments and Risks haven't changed, haven't changed much, and have changed and provide a summary table of common risk themes and which projects face those risks.*

Copilot Business produced that summary table in under three minutes. To verify its accuracy, we read a sample of the text-based risks assessments across the six periods, and after confirming the sample set appeared accurate, we had the project managers confirm the GenAI's assessment. Both validations confirmed that we could have confidence in the results when we run the prompt, but we still read it for accuracy confirmation and to get a sound understanding of the portfolio prior to distribution.

The previous big dataset examples primarily have been qualitative and applied to unstructured data. The next set of examples will expand to quantitative analysis and primarily apply to structure datasets.

My US Air Force Academy B.S. in Economics covered econometrics, which is statistics on steroids. T-tests, F-tests, and LaGrange were drilled into us until they became second nature, but over time and through dependency on statistics packages, my skills atrophied some. With the advent of GenAI, there was a potential that GenAI could augment my current level of econometric skills, but not without verification of the GenAI's abilities first—"trust, but verify," is one of President Reagan's famous phrases.

My team consolidated the KPIs and text-based assessments the project managers made on eighty-seven projects over forty-nine reporting periods. This amounted to over twenty-two hundred records, which is a "gold mine" for statistical analysis! I apologize if I appear too enthusiastic about this, but I rarely come upon datasets like this, and their predictive potential holds significant value to decision makers. But could I engineer a prompt to have GenAI perform

accurate statistical analysis? The answer was yes . . . and now I potentially will not have to buy another statistics package or build another statistics model.
It took approximately twenty hours to build an Excel-based model that could handle that much data, accommodate each new period's input without manual labor, and produce and update the r-squared goodness-of-fit value (the predictive element of statistics) each time the project managers completed a reporting cycle. The r-squared goodness-of-fit value is the percentage of variability in the dependent variable is driven by variability in the independent variable.

Our KPIs offer two primary predictive cases: 1) forecast the likelihood of a change in the total cost, the dependent variable, based on the variability in the other eight variables, the independent variables, and 2) forecast the likelihood of a change in the go-live date, the dependent variable, based on the variability in the other eight variables, the independent variables. In essence, forecast which projects are likely to have a cost overrun or be late in going live.

The Excel-based model then served as the test case to confirm that both Copilot and Perplexity® were capable of correctly calculating the r-squared goodness-of-fit value for each project based on its structured data. Both GenAI tools calculated it correctly and Perplexity®'s Sonar stated that its and the Excel-based model's r-squared values matched to six digits.

The prompt to have the GenAI tools calculate the r-squared value did not require iteration and was simple: "As a statistics-based project manager calculate the goodness-of-fit value for the Total Cost and Go-Live Date risk and compare it to my calculation. I'll load the file with the data next." In under three minutes each tool calculated the r-squared values and provided these two responses:

- Perplexity® Sonar: I've confirmed that your Excel R^2 values are 100% accurate
- Microsoft® Copilot: You have already run the correct regressions inside the file

Notice that the phrasing of both Sonar's and Copilot's responses gave the impression that the tools thought they were confirming my work. In reality, my test cases existed to confirm that the two GenAI tools could perform statistical analysis correctly—it became an issue of "who is checking whom."

Once past the uneasy feeling that GenAI thought it was the standard against which my analysis was being tested, and having confirmed that GenAI accurately produced both qualitative and quantitative results, it was possible to leverage GenAI to put both qualitative and quantitative together—much faster than the EPMO could do by hand.

Companies need to know the status, assessment, and forecast of a project's scope, cost, and schedule. Project managers typically are the ones who provide all three, and judgment is involved. Judgment is open to interpretation, interpretation leads to discussions, and the executive discussions that result from the interpretation lead to informed decision making about adjusting, continuing, or cancelling projects.

One means to confirm the project manager's judgment and remove bias is quantitative analysis via statistics. Forty-nine reporting periods provides enough project-specific data to produce results that are statistically significant within a reasonable margin of error, similar to how presidential election surveys interview enough people to be able to state "Candidate A: 46%, Candidate 1: 42% (with a +/-3% margin of error)."

Based on GenAI's accurate qualitative assessment of the project manager's text-based risk reports and qualitative, statistics-based assessment of the project KPIs, GenAI can determine the top five projects at risk of overrunning cost and the top five projects at risk of extending their go-live dates.

Project	Why It Ranks Top-5 (Data + Comments & Risk Substantiation)
Project 1	Repeated negative/positive cost swings and high cost-risk indicators. Comments and Risk repeatedly cites **extended QA/UAT cycles, unresolved defects, vendor transition impacts, and additional unfunded CAPEX exposure**, all classic drivers of cost overrun.
Project 2	One of the strongest cost-risk signals. Comments and Risk references **steel-index pricing, freight volatility, pending vendor estimates, manufacturing constraints, and multiple change requests**, indicating structurally unstable cost drivers.
Project 3	Sustained high cost-risk indicator. Comments and Risk documents **contingency funding likely, scope complexity beyond estimates, descoping discussions, and approved/pending change requests**, all pointing to forecasted EAC growth.
Project 4	Cost indicator elevated with multiple large adjustments. Comments and Risk notes **resource onboarding delays, QA rework, additional labor not in baseline, and formal CRs for budget/timeline**, making further cost creep probable.
Project 5	While partially closing, cost risk remains high. Comments and Risk highlights **unresolved vendor invoices, encumbered funds, NCR support/maintenance costs, and red KPIs**, meaning final actuals are still at risk of exceeding baseline.

Figure 4: Top 5 Project with Cost Risk

Error! Reference source not found. shows the Copilot-produced summary, project names redacted, which serves as the starting point for discussion about portfolio cost risk and how to mitigate it (Copilot Business. Response to "As a statistician, go through all . . . data and list the top 5 projects with cost risk.", 2026). It contains not only a summary of the project managers' text-based risk assessment but also references the impact of the cost-risk KPI that the project managers reported over the forty-nine periods.

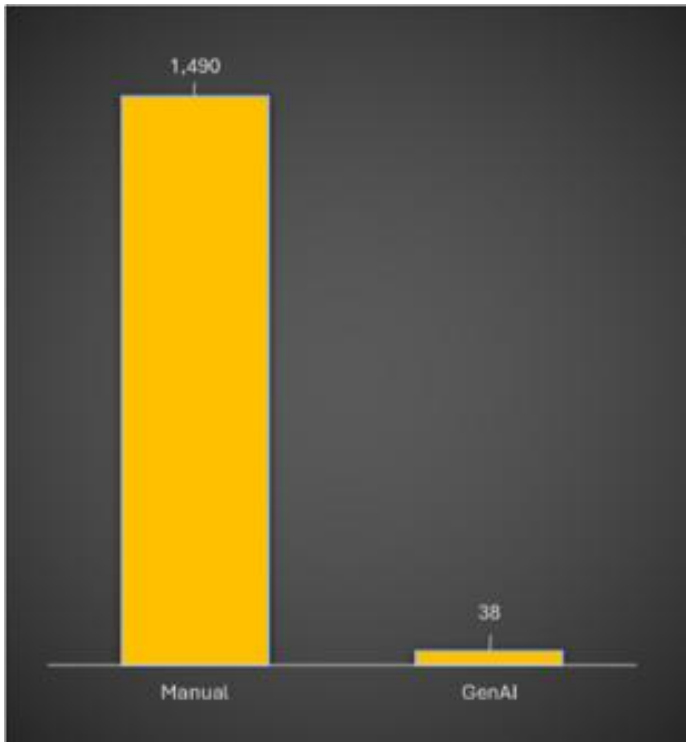

Figure 5: Copilot's Efficiency

In addition to being able to correctly perform and summarize the qualitative and quantitative analysis, Copilot also did it more efficiently than I can—a staggering 97.4% reduction in cycle time (**Error! Reference source not found.**). The process to manually perform the qualitative and quantitative analysis took around fifteen hundred minutes and included these steps 1) build the statistical model, 2) assess trends (quantitative), 3) incorporate comments (qualitative), and 4) summarize. The Copilot Business-augmented process took about forty minutes. It divested of the "build-the-statistical-model" step—about twenty hours of labor. The augmented process also required me to validate the results, which took about thirty minutes, and since I'm accountable for the product, it served as a means for me to gain comprehension of the summary so I'm not a mere talking head when presenting and discussing the top five projects at risk to overrunning cost.

Based on the accuracy and significant efficiency gain when using GenAI, it is highly likely that I will not have to take the hours required to build another statistics model since GenAI demonstrated that it correctly calculated the r-squared to six digits for the test set of eight-seven

projects. While both Microsoft® Copilot Business and Perplexity® Sonar passed the statistics test, it is wise to reconfirm periodically, like we do annual reviews with team members, and perform an initial test on any new GenAI starts being used for statistical analysis.

Annual reviews permit us to assess, document, and provide feedback on people's skills, aptitude, and motivation. The next section addresses motivating people to adjust to and adopt GenAI.

Motivating GenAI Adoption

Leadership models and examples are documented in ancient texts such as Sun-tzu's **Art of War** written in the fifth century BC and the **Old Testament**, which was written before that. What all texts on leadership have in common is pointing out that there no characteristic: physical, geographic, gender, era, or age of the leader common to leadership—anyone can do it!

Project managers may not be in an official leadership position, but there are many other kinds of power besides positional. Referential and influential powers are two that project management professionals frequently leverage.

One qualification of being the leader is that the leader must understand, believe, and embrace the change. Former four-star general and Secretary of State Colin Powell states is this way, "The leader starts to change institutional brainware by setting the example and changing his own" (Powell, 2012, p. 109). The "brainware" Powell refers to is the leader's knowledge of the why and means, belief that it is a valid path to take, and self-motivation to do it. With those elements in place, a leader can lead . . . if the team is motivated.

Motivational triggers can take many forms, and ultimately, the best form of motivation is internal motivation. This happens when several interactions between the leader and team forms a valid bond based on the team members' belief that the leader cares about each of them on a personal level and the team member is willing to follow the leader. A common situation where someone knows another cares for him/her but is unwilling to follow that individual, is the parent-child relationship. I have numerous fun memories of bike rides with my children, who cared deeply for me. Often, I let them lead the bike ride, but depending on the destination, when we needed to be back home, terrain, or some other factor, I would have to take over the leadership role

because in many situations, they did not yet have the wisdom to lead. People will only follow inwardly when they can trust the leader in many areas.

Given that the leader has the skills, background, and self-motivation to lead, one deep-reaching approach to inducing motivation is change is self-preservation. Transformation consultants and salespeople refer to this as the "burning platform" that motivates internal commitment to embrace the change, or make the purchase, respectively. The burning-platform approach must be leveraged sparingly since discussing it too frequently can be demotivating, despite the strength of the relationship between the leader and the team.

An instrument readily available to serve as a self-preservation motivator is Anthropic's report titled, *Data, Labor market impacts of AI: A new measure and early evidence*, which Anthropic updates periodically as more observed AI usage data come in. It contains a "Theoretical Capability and Observed Usage" chart shown in **Error! Reference source not found.**.

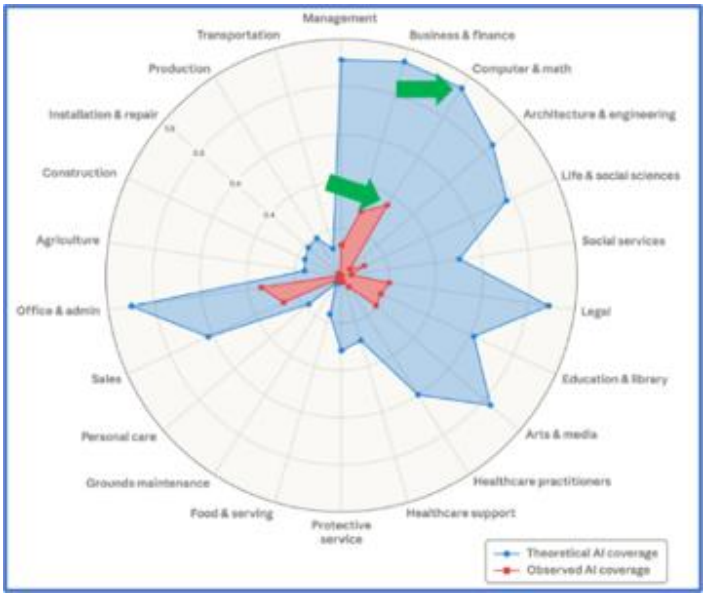

Figure 6: Theoretical Capability and Observed Usage

The Theoretical Capability, represented by the blue area, is what percentage of a profession's functions GenAI can perform. The Observed Usage, represented by the red area, is the percentage of a profession's functions that Anthropic® observes users entering prompts into its Claude GenAI to perform on their behalf.

Anthropic groups "IT Project Management" into the "Computer and math" profession. Unfortunately, as of March 2026, Anthropic's report did not provide the theoretical and observed usage percentages specific to IT Project Management. Therefore, only the parent's theoretical usages of ~97% (outer arrow on the diagram) and observed usage of ~35% (inner arrow on the diagram) are available. This does not mean that Claude is performing ~35% of all management functions, it merely means that people have prompted Claude to perform 35% of the computer and math functions.

After discussing this during a GenAI team meeting, one project manager approached me one-on-one and said, "Be careful what we wish for, we might get it!" I paused, letting him know I was thinking about was he said and then responded, "I think GenAI is here to stay. The purpose of our meetings is to stay ahead of for the benefit of our company and ourselves." He agreed.

Another technique available to drive internal motivation is that of shared leadership. A former US Army sergeant major explains it this way, "Though you might be in charge, it takes a leadership 'team' to be successful. Some people believe this means surrendering authority; it doesn't. If you're in charge, then you already have the authority, and you are responsible for everything that happens, good or bad. Giving leaders the power to make decisions within the rules and scope of the mission only makes you a better leader" (Spisso, 2019, p. 18.). As our EPMO has been meeting to discuss and exemplify GenAI's use for over two years, both my EPMO peer leaders and a few project managers and business analysts have led discussions and demonstrations that furthered the overall adoption of GenAI.

Additionally, we always end the thirty-minute GenAI meeting with five minutes of open-mic time for anyone to share successes and/or failures as s/he has used GenAI either in the workplace or in personal life. Examples have ranged from drafting/refining emails to writing a business case analysis on the professional side and from planning a honeymoon to gaining insight on a minor medical condition on the personal side. Occasionally, an EPMO member will offer to do a demonstration of how s/he has used GenAI to do work faster but still at the same quality point. As everyone sees and hears others using GenAI in both arenas, more adoption happens to the benefit of the person, the project management profession, and the company.

Summary

Private GenAI is available and companies are incentivizing its use. EPMOs, PMOs, and project managers need to adapt to the new environment. A proven path to implementing GenAI is to

1. Use the agile philosophy of failing fast to determine which private GenAI offering and features work for your situation

2. After gaining confidence engineering prompts effective with small data, move to big data, both unstructured and structured, to get big results. Some cycle times can be reduced by 97% or more

3. Lead by example—change yourself first, build trust, and transform the team to leverage GenAI

Our EPMO, with a $550M portfolio, used this approach to get its members—admin to leadership—to adopt GenAI. By employing this approach, finding or generating examples specific to your environment, and properly motiving your team, your office can transform to a GenAI-augmented workplace increasing value to your company and clients, and team members.

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About the Author

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Greg Saunders is a Disciplined Agile Senior Scrum Master and PMP serving at the Army and Air Force Exchange Service, the Exchange, which is an $7B international retailer for America's Soldiers, Airmen, and Guardians. He's currently the manager of the Exchange's Program and Project Portfolio Governance office, setting policy for and managing a $550M portfolio of 90 programs, projects, and initiatives. Previously at the Exchange he 1) served as PMO head with a team of 22, 2) served as the lead PM for the Exchange's largest program—replacing the accounting systems; 3) worked with PM, governance, and system analyst leads to architect the transformation of the Exchange's program management approach; 4) served as the systems portfolio manager of 51 primary HR, payroll, & data warehouse systems; and 5) served as the PMO head for a 16-person team managing a $150M portfolio of 60 projects.

Prior to joining the Exchange, he ran a $2.5M/year business in a top-tier consultant firm. During his USAF career he re-established the Denver-based Air Reserve Personnel Center's (ARPC) PMO; led the upgrade to ARPC's portion of the Air Force Personnel Center's call center that supports over 6 million reservists, retirees, and their surviving spouses; and as a colonel at the Pentagon served as both the USAF Reserves Comptroller and the Reservist to the AF CIO Director for Cyberspace Capabilities and Compliance, overseeing a team of 60 managing the USAF's cyberspace capabilities, policy, and compliance. Over his 35-year career he has also become a Certified Agile Practitioner, been certified in ITIL Foundation, and been certified by the Air Force as a Lean, Six Sigma Black Belt. He can be contacted via Linked at https://www.linkedin.com/in/greg767/.