When AI Joins the Team: Measuring Perceived Productivity Gains from Generative AI in Project Management

Ole Mehlert, Sibylle Kunz, Claudia Hess
IT & Engineering / Management
IU International University of Applied Sciences
Erfurt, Germany
e-mail: ole.mehlert@iu-study.org; sibylle.kunz@iu.org; claudia.hess@iu.org;

***Abstract*— Amid persistent productivity challenges in Project Management, Generative Artificial Intelligence is emerging as a powerful tool for administrative and information-intensive tasks. However, empirical evidence of its actual productivity impact remains fragmented and lacks a unified measurement framework. This paper addresses this foundational gap by proposing a multidimensional instrument to measure perceived productivity. An initial field test with project management professionals served to examine the instrument's practical usability, provide an initial reliability check, and generate preliminary descriptive findings illustrating its potential value.**

Keywords- project management; generative artificial intelligence; productivity.

I. Introduction

Much of Project Management (PM) work involves administrative and information-intensive tasks like status reporting, stakeholder communication, risk analysis, and the preparation of decision briefs [1]. Performed under time pressure, resource constraints, and increasing complexity, these duties create persistent productivity challenges, especially in synthesizing and communicating large volumes of information efficiently. Generative Artificial Intelligence (GenAI) directly targets these PM activities with its ability to summarize text, structure data, and prepare reports. However, its use introduces significant uncertainties, including data protection, user competency, and the risk of "hallucinated" outputs. Furthermore, AI-generated content often requires verification and rework, which can offset anticipated efficiency gains. This creates a central challenge for organizations: developing ways to assess GenAI's perceived and true net benefits in practical PM contexts.

Initial evidence suggests GenAI is used for simple, standardized PM tasks rather than complex decision-making [2][3]. While efficiency gains are frequently reported, empirical research remains fragmented, often focusing on isolated tasks and lacking multidimensional measures that capture quality or cognitive relief alongside time savings. Furthermore, it remains unclear how perceived gains are moderated by a project manager's experience level.

To address these gaps, this research develops a multidimensional measurement instrument for perceived productivity gains in PM. We demonstrate its application through a field test with 97 PM professionals, offering preliminary descriptive findings, an initial reliability indication, and groundwork for future validation and causal research.

The paper is structured as follows. Section II reviews the theoretical context of GenAI in PM and productivity measurement. Section III details the methodology and instrument development. Section IV presents the analysis of the survey data from the field test. Then, Section V discusses results and highlights areas for future research. Finally, Section VI summarizes the paper's core contributions.

II. Theoretical Background

A. Patterns of GenAI Adoption in PM

Recent studies examine the use of GenAI in PM and its productivity implications. What began as exploratory experimentation is evolving into adoption across industries. A global study by the Project Management Institute (PMI) in January 2024 surveyed 500 project professionals across 18 industries in 12 countries, all reporting GenAI use in their projects [4]. The study highlights its growing relevance in PM and identifies four user types:

- **Explorers** use GenAI selectively and experimentally in isolated project tasks.
- **Adapters** apply GenAI regularly to support recurring and moderately complex activities.
- **Innovators** use GenAI extensively across tasks to enhance efficiency and creativity.
- **Trailblazers** embed GenAI strategically and systematically into complex and high-impact tasks.

The categorization emphasizes that GenAI adoption in PM is not uniform but varies in scope, depth, and organizational integration. More intensive adoption is linked to stronger positive assessments of GenAI's impact on key project-level outcomes, such as scope, schedule, cost, and quality management [4]. A similar pattern emerges at the individual level: respondents with high GenAI usage report better outcomes in productivity, collaboration, creativity, problem-solving, and overall effectiveness than those with more limited, exploratory use.

Although the PMI study distinguishes multiple performance dimensions, these are captured broadly. This creates an opportunity to further specify and operationalize productivity aspects for concrete PM activities. Such a systematic investigation requires two key components: a classification framework for GenAI use cases and a model for measuring their productivity impact.

B. Classifying GenAI Use Cases in PM

To classify GenAI use cases in PM, established project management paradigms were first evaluated. Categorizing cases by project lifecycle phases proved unsuitable for cross-industry analysis due to the lack of a standardized phase model across PM bodies (e.g., PMI, PRINCE2), industries, and methodologies (e.g., Agile, Waterfall). Comparability is further limited as activities, such as risk management occur throughout the lifecycle, blurring phase boundaries. An alternative grouping by functional category [5][6], was also considered but found either too vague or too industry-specific. Instead, the PMI's AAA framework was selected, which organizes GenAI use cases in PM into three tiers, based on their increasing complexity and the corresponding need for human intervention [7].

- **Automation** represents the lowest level of complexity, where GenAI independently executes well-defined, rule-based tasks. The human role is typically limited to initiating the process and reviewing the standardized output, such as automated meeting minutes or status reports.
- **Assistance** describes tasks of medium complexity where GenAI acts as a support tool, providing drafts, analyses, or recommendations. The human practitioner then evaluates, contextualizes, and makes the final decision. Examples include generating initial cost estimates or performing risk data analysis.
- **Augmentation**, the highest level of complexity, involves a co-creative partnership in which GenAI enhances human cognitive capabilities. GenAI is used to simulate complex scenarios, identify novel patterns, or generate strategic options, while the human retains full responsibility for the final decision. Augmentation includes strategic tasks like managing project portfolios.

C. Measuring Dimensions for AI Productivity in PM

To measure the impact of GenAI usage, [8] provides a structure. Kunz & Hess argue that both analytical and generative AI can improve productivity across three primary dimensions: **time, cost, and quality**. Applying specific measures to these dimensions allows AI-related productivity gains to be calculated. These dimensions directly align with the foundational "iron triangle" of PM, which conceptualizes project success as the balance of these three constraints [4]. By examining the perceived effects of GenAI through the lens of the iron triangle, we can systematically assess its *direct* contribution to the core goals of PM as understood by practitioners.

However, a comprehensive assessment of GenAI's benefits requires moving beyond the traditional constraints of the iron triangle. The literature indicates that GenAI usage also exerts *indirect* effects on several strategic dimensions by fostering long-term capabilities. First, it enhances **innovation and creativity**, particularly during ideation phases where it can rapidly generate diverse concepts [9]. Second, it optimizes **decision-making** by enabling faster, data-driven analysis, with studies showing that human-AI collaboration yields the highest improvements in decision quality [10][11]. Finally, GenAI strengthens **knowledge management** by improving the creation, structuring, and application of organizational knowledge, thereby reducing information silos and freeing up employees for higher-value learning tasks [12][13].

D. Synthesis and Identification of the Research Gap

A systematic analysis of current GenAI research reveals two critical gaps. First, studies of GenAI's impact are predominantly qualitative. The research scope is fragmented, examining either discrete, simple tasks (e.g., generating meeting minutes), or ill-defined categories (e.g., "planning") [2][3]. This lack of a unified, quantitative framework for measuring productivity provides a partial and skewed view of GenAI's utility.

Beyond *what* is measured, a second critical gap concerns *who* is using the technology. First, digital competency is a key determinant [14]. Counterintuitively, less competent users tend to delegate more complex tasks (e.g., risk management) to AI and assign it a more active, rather than merely supportive, role in the problem-solving process. Second, PM experience also shapes the professional use of GenAI [15]. Seasoned project managers apply GenAI to strategic and complex problems, while novices use it for foundational tasks and skill development. This suggests experienced professionals can better integrate new technologies to exploit their full potential.

Consequently, the central challenge is the lack of a multidimensional instrument that measures perceived gains while also accounting for the moderating effects of user experience. Therefore, empirically investigating GenAI's impact requires first developing this tool.

E. Research Questions

To address the identified research gap, this paper is guided by the following research questions:

RQ1 (Methodological): How can the perceived productivity gains from using GenAI in PM be operationalized into a multidimensional measurement instrument?

RQ2 (Exploratory): Based on this new instrument, what are the initial descriptive findings regarding perceived productivity gains across different PM tasks, and how do these perceptions appear to differ based on user proficiency?

III. Methodology

This section details the systematic process used to develop, refine, and conduct an initial field test of the measurement instrument.

A. Measurement Development

The measures for this study were developed based on the theoretical foundation from Section II. The operationalization process involved two key principles: first, grounding our measures in the existing literature, and second, ensuring items were specific and behavior-oriented rather than abstract. The survey instrument was developed and administered in German. The English item formulations presented in this paper are translations prepared for reporting purposes only. The following sections detail the operationalization of the different constructs.

1) Self-Assessment of GenAI Proficiency in PM: To assess GenAI proficiency, a single-choice question was developed based on the PMI's four-part user typology presented in Section II.A. The defining characteristics were adapted and formulated as first-person statements, forming a hierarchy of GenAI integration:

- **Explorer: "**I use generative AI sparingly in my projects for selected, straightforward tasks (e.g., brainstorming, text creation, and summarization)."
- **Adapter: "**I use generative AI regularly in my projects for recurring, moderately complex tasks (e.g., creating project plans, risk assessments)."
- **Innovator: "**I use generative AI extensively in my projects across a wide range of tasks and optimize its application (e.g., project budgeting, resource planning)."
- **Trailblazer: "**I use generative AI strategically and systematically in my projects for complex and critical tasks (e.g., forecasting project outcomes, automated decision-making)."

Respondents were asked to select the statement that best described their usage pattern.

2) Operationalizing GenAI Usage: To enable a comparative analysis of GenAI usage across different industries and methodologies, a standardized framework was required. This study adopted the AAA-Framework (Section II.B) for its clear, hierarchical structure and its focus on the nature of use rather than specific contexts. To operationalize this framework, a representative PM task was selected for each category. These tasks serve as proxies to empirically measure and compare GenAI application across different levels of complexity.

For the automation category, we selected *creating meeting minutes*. In this process, GenAI autonomously transcribes discussions and generates structured summaries with key decisions and action items, requiring only a final human review. This choice is validated by its explicit citation as an automation example by PMI [7], and its successful application in PM [14].

We chose *stakeholder communication* for the assistance category. GenAI is used to draft communications like emails or status reports based on project data. The process is characterized by a medium level of complexity, as it requires significant human intervention for contextual adaptation and refinement. Its selection is also supported by its documented success as a GenAI application in PM [14] [16].

For the augmentation category, we selected *project portfolio decision*. In this strategic task, GenAI analyzes project proposals to generate data-driven recommendations. The process requires deep human-AI collaboration, as experts, typically senior management, must provide contextual knowledge and retain final judgment. This synergy on a high-stakes decision makes it a prime example of augmentation.

3) Operationalizing Productivity Gains: We conceptualize perceived productivity gains from GenAI as a multidimensional latent construct. It is latent because it is not directly observed but inferred from indicators like time savings and quality improvements as discussed in Section II.B. It is multidimensional because it encompasses several distinct yet related value contributions, not just a single effect. Consequently, a single percentage-based estimate (e.g., "To what extent has GenAI increased your productivity?") is inadequate, as it wrongly assumes a unidimensional effect and forces respondents to aggregate heterogeneous benefits, thus reducing measurement validity.

Therefore, our study assesses perceived gains indirectly using multiple task-specific indicators for each theoretical dimension, measured on a five-point Likert scale ranging from strong disagreement to strong agreement. This approach ensures contextual validity while consistently measuring the underlying construct. The operationalization is illustrated by the automation task. Following the introductory prompt "Thinking back to the creation of meeting minutes: How helpful was the use of generative AI in this context for you?"., the task-specific items displayed in Table I were presented. The same approach was taken for the assistance and the augmentation tasks.

TABLE I. AUTOMATION: CREATION OF MEETING MINUTES

Task: Meeting Minutes	Dimension
I produce more precise and less error-prone meeting minutes that clearly summarize the discussed content and assign tasks to the appropriate persons.	Quality
I am able to reduce the effort required for manual documentation and follow-up, thereby decreasing personnel and resource expenditure.	Cost
I provide meeting minutes significantly faster after the meeting and require less time for their preparation.	Time
I structure meeting minutes more consistently and make them easier to retrieve, thereby improving knowledge sharing.	Knowledge Management
I automatically identify recurring topics or patterns and thereby receive impulses for improvements.	Innovation & Creativity
I document decisions more precisely, making them easier to understand through clear summaries and supporting arguments.	Decision-Making

B. Survey Design

The questionnaire was structured according to established survey design principles to ensure a logical flow and a positive respondent experience [17]. Questions were arranged in order of increasing difficulty, and the layout was organized into distinct thematic blocks. The survey was presented in the following order: (1) an introductory title page, (2) the block of screening questions, (3) a section for the self-assessment of GenAI usage in PM, (4) a block for demographic information, (5) the main section measuring the construct of perceived productivity gains, (6) an open-ended question about further applications beyond those mentioned, and (7) a concluding thank-you page. Note that for the main assessment in step (5), and to ensure relevance, only participants who confirmed prior GenAI use for each task (which was briefly described) proceeded to the evaluation.

Prior to the main launch, three external participants evaluated the survey for clarity and usability. Based on this pretest, several formulations and scale labels were refined for clarity, and the layout was adjusted.

C. Study Design and Data Collection

To collect data for the initial field application of our newly developed instrument, a quantitative online survey was conducted. The German-language survey was distributed between November 25 and December 29, 2025, targeting PM professionals with prior experience using GenAI in their work. The average completion time for the questionnaire was 5 minutes and 42 seconds.

Participants were recruited via the professional networking platform LinkedIn. Participation was voluntary and unpaid. This recruitment method was selected due to the platform's large number of thematically relevant groups with a direct professional connection to PM and the use of GenAI, which allowed for targeted recruitment. A key component of the distribution strategy was the dissemination of the survey through the PMI Chapter Germany e.V., reaching over 5,000 members. This collaboration was particularly appropriate, as the present study references PMI frameworks.

D. Sample Composition

The survey was designed to target a specific professional demographic. Eligibility was strictly controlled by the three screening questions, ensuring the sample consisted exclusively of PM professionals located in Germany, Austria, or Switzerland who had prior experience using GenAI for PM tasks. From a gross sample of 113 respondents, 16 were removed by the screening questions, leaving a final net sample of 97 participants for analysis. The sample is predominantly composed of professionals in the earlier stages of their PM careers, with a significant majority (62.9%) reporting five years of experience or less. The most seasoned cohort—those with over a decade of experience—was the least represented, accounting for just 13.4% of the total sample. Table II summarizes the sample characteristics.

TABLE II. SAMPLE CHARACTERISTICS: YEARS OF EXPERIENCE IN PM

Years of Experience in Project Management	**Sample**	
	Frequency N	***Percentage (%)***
< 1 year	12	12.4%
1-5 years	49	50.5%
6-10 years	23	23.7%
11-15 years	4	4.1%
> 15 years	9	9.3%
Total	**97**	**100.0%**

An analysis of the participants' current roles shows a clear predominance of Project Team Members, who constitute nearly half of the sample at 48.45% (n=47). The next most common roles were Project Leader/Manager at 14.43% (n=14) and Project Management Office (PMO) members at 12.37% (n=12). All other roles were represented in single-digit percentages: Sub-project Leaders (6.19%, n=6), Functional/Line Managers with project responsibility and External Consultants/Service Providers (both 5.15%, n=5), Scrum Masters/Agile Coaches and Program/Portfolio Manager (both 3.09%, n=3), and Product Owners (2.06%, n=2). The fact that the 'Other' category was not selected (0.00%) indicates the provided role options comprehensively covered the sample population.

The industry distribution, based on categories from a PMI study [2], shows a heavy concentration in the Information Technology sector, representing 23.7% of all responses. Significant cohorts also came from Aerospace (15.5%) and Consulting (14.4%). Other notable sectors included Automotive, Logistics, and Telecommunications, with minimal representation from remaining industries like healthcare, construction, and pharma. Note that participants were permitted to select multiple industries.

IV. RESULTS

This section presents the descriptive statistics and initial empirical findings from the online survey.

A. Self-Assessed Proficiency

The self-assessment of GenAI proficiency reveals that the majority of users are in the intermediate stages. “Adapters” form the largest cohort at 43.3% (n=42), followed by “Innovators” at 30.9% (n=30). Conversely, early-stage “Explorers” (20.6%, n=20) and expert-level “Trailblazers” (5.2%, n=5) represent the smallest groups. This indicates that while deep, complex usage is still rare, a significant majority of respondents have moved beyond initial experimentation and possess solid experience applying GenAI in PM tasks.

Furthermore, a Spearman's rank correlation analysis revealed a significant positive relationship between years of PM experience and self-assessed GenAI proficiency ($\rho = 0.546$, $p < 0.01$, n=97). Following [18], this correlation strength is interpreted as moderate. This finding indicates that as a project manager’s experience increases, so does their self-reported GenAI proficiency. This suggests that extensive professional experience in PM may foster a more rapid development of competency in applying these AI tools in the PM context.

B. GenAI Usage in PM

GenAI adoption varies significantly across the three tasks, which were selected as proxies to represent different levels of complexity. The analysis shows a clear divide between administrative and strategic tasks. The most common application by a wide margin is the creation of meeting minutes, where 84.5% (n=82) of participants have experience. In stark contrast, adoption rates for more complex functions are significantly lower. The use of GenAI for stakeholder communication drops by more than half to 41.2% (n=40), while its application in supporting project portfolio decisions is even less frequent at 33.0% (n=32).

Notably, four participants reported zero usage across the specific PM tasks listed in the survey. However, these individuals were retained in the final sample. This decision was made because, in a concluding open-ended question, they described other valid applications of GenAI in their PM work that were not covered by the predefined tasks.

C. Perceived Productivity Gains

To assess perceived productivity gains, participants rated the benefit of GenAI for each of the three tasks (Meeting Minutes, Stakeholder Communication, Project Portfolio Decisions) on a 5-point Likert scale across six dimensions: Time, Quality, Cost, Decision-Making, Innovation, and Knowledge Management.

1) Preliminary Instrument Reliability: Before analyzing the mean scores, we assessed the internal consistency of the item sets for each task. A composite reliability score (Cronbach's Alpha) was calculated for the six-item "Productivity Gains" construct for each of the three tasks. The scale for "Meeting Minutes" showed acceptable consistency ($\alpha = 0.704$), while the scales for "Stakeholder Communication" ($\alpha = 0.863$) and "Project Portfolio Decisions" ($\alpha = 0.852$) demonstrated good to excellent consistency, interpreted according to Blanz (2015, p. 256). These results provide an initial indication of the internal consistency of the aggregated perceived productivity measures for each task.

2) Descriptive Findings: Table III shows the resulting mean scores and Standard Deviations (SD) for the three tasks. Across all three tasks analyzed, the perceived benefits were consistently dominated by direct, efficiency-related dimensions. Time emerged as the highest-rated perceived productivity gain. Cost and Quality followed closely, with Cost rated slightly higher for meeting minutes and stakeholder communication, while Quality marginally exceeded Cost for project portfolio decisions. The indirect dimensions (Decision-Making, Innovation, Knowledge Management) consistently received lower scores, although their specific order varied depending on the task.

TABLE III. PERCEIVED PRODUCTIVITY GAINS

Dimension	***Meeting Minutes***		***Stakeholder Communicat.***		***Project Portfolio Decision***	
	Mean (N=82)	***SD***	***Mean (N=40)***	***SD***	***Mean (N=32)***	***SD***
Time	4.33	0.546	4.18	0.594	3.91	0.734
Cost	4.20	0.576	3.97	0.577	3.72	0,.581
Quality	4.07	0.466	3.80	0.723	3.75	0.672
Decision-Making	3.80	0.617	3.47	0.877	3.63	0.707
Knowledge Management	3.68	0.564	3.72	0.784	3.41	0.712
Innovation & Creativity	3.67	0.589	3.63	0.774	3.63	0.660
Composite score	**3.96**	**0.357**	**3.80**	**0.521**	**3.67**	**0.514**

Considering the composite score, the application of GenAI for creating meeting minutes received the highest rating (3.96), followed by stakeholder communication (3.80). The task of supporting project portfolio decisions received the lowest rating (3.67), though the score remained significantly above the scale's midpoint of 3.0.

V. DISCUSSION

A. Preliminary Findings and Their Implications

Although the field test is constrained by its relatively small sample size and therefore limited generalizability to the broader population of PM professionals, the analysis revealed noteworthy findings. First, the results suggest that the PM professionals in our sample are pragmatic adopters, using GenAI primarily for low-risk, high-return administrative tasks. This cautious adoption pattern, especially for complex strategic tasks, aligns with literature on initial AI integration [2][3].

Second, consistent with [14], our data hints at heterogeneous GenAI use across experience levels. The tendency for some novice users to apply GenAI to advanced tasks suggests a potential "competency gap" risk, where the tool is used without sufficient domain expertise for verification of AI outputs. Our data offers some support for this, as novice 'Explorers' attempted advanced tasks like portfolio decision-making.

Finally, the perceived productivity gains appear inversely related to task complexity. The highest productivity gains are perceived in standardized administrative tasks like meeting minutes, where the need for human judgment is low. However, even the most complex task was rated positively, suggesting that the surveyed PM professionals find value in using GenAI as a supportive tool across different levels of PM work. Future work should include a more detailed analysis of differences based on experience level, both in PM and in the use of GenAI.

B. Lessons Learned in Instrument Development

From deploying the survey in a first field test, several lessons for instrument development emerged. First, operationalizing GenAI use via proxy tasks involves a trade-off. Using representative tasks allows us to ask for concrete productivity gains, but it constrains generalizability. Respondents may use GenAI heavily in other tasks (as four users noted in the open-ended responses) but not in the specific task presented. A future iteration could include a broader task battery per AAA category, or let respondents select the task(s) they use most within each category. Moreover, as the ratings were restricted to actual users of each task, subgroup sizes may be uneven as in our data. This affects reliability estimates, comparability, and statistical power for subgroup analyses.

Second, the translation of perceived productivity into measurable indicators requires further clarification. Using multiple dimensions improved conceptual coverage but also necessitates clearer boundaries to avoid overlap. Interviews could test how respondents interpret and distinguish these dimensions, particularly for indirect effects. In addition, rework (e.g., due to GenAI hallucinations or compliance constraints) should be explicitly accounted for, as it may offset initially perceived productivity gains. Future refinements could include counter-items capturing

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verification effort, rework frequency, and confidence in output correctness, especially for high-stakes tasks.

Third, while self-classified GenAI proficiency is pragmatic, a future iteration could consider adding a small set of objective or behavioral indicators (e.g., frequency of use, number of tools used, prompt complexity) to triangulate proficiency. Together, these lessons suggest directions for the next instrument iteration. Moreover, validation steps should be planned that go beyond the initial internal consistency checks performed in this study.

VI. Conclusion and Future Work

A central challenge in AI productivity measurement is moving beyond generic self-assessments to a concrete, multidimensional measurement. To address this for PM, we developed a survey instrument for assessing perceived productivity gains, grounded in research on GenAI usage and AI productivity measurement. Crucially, our instrument operationalizes productivity by distinguishing between direct gains (time, cost, quality) and indirect gains (e.g., improved decision quality), allowing for an assessment that captures both immediate task efficiency and long-term capability building. To ground these measurements in practice, they were applied to three proxy tasks representing distinct modes of human-AI interaction: automation, assistance, and augmentation. The instrument was empirically applied in a field test with 97 German professionals with practical GenAI experience in PM. The field test indicates that the measurement approach is practically usable and provides a basis for further refinement and validation.

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