Artificial Intelligence Use in Project Management [1]

Issues That Project Managers and Other Members of the Project Team Should Be Aware, Part 3 [2]

By Ivano di Filippo, Dr. Josh Ramirez,
Darrell Mesa, Claudia Alcelay and Rebecca Winston

Italy & USA

Biases and Data in Project Management

Introduction

Artificial intelligence (AI) is becoming increasingly important in project management due to its ability to potentially improve decision-making speed and accuracy. However, reliance on AI brings significant challenges and risks, particularly concerning biases that can influence the generated responses. Biases present in the data used to train AI models can be unknowingly encoded into the models themselves, leading to partial or distorted responses (Mehrabi et al., 2021). This issue is particularly relevant for project managers who might be making critical decisions based on information provided by AI systems.

The implications of biases can manifest in various ways:

- **Data bias:** When training data can reflect social prejudices, AI responses can perpetuate these biases. A study by Bender et al. (2021) highlighted how language models can amplify biases present in training data. For example, if a dataset contains fewer representations of certain populations, the generated responses might be less accurate or even discriminatory towards those groups.

[1] *Editor's note: This article is an introduction to a series of articles by the authors on the use of artificial intelligence (AI) in the project management field. While the authors recognize the rapidly growing attention on the potential power and impact of AI on project management, they also want to point out the risks of assuming AI and human intelligence are or can be equated. The authors have previously researched and published on topics related to neuro-behavioral issues and cognitive intelligence in project management.*

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- **Outcome bias:** Additionally, data in open-source AI systems might have been selected to achieve specific outcomes. This bias poses a risk for project managers, especially if such data is used to plan schedules or identify and treat project risks.

Examples:

- **Representation Bias:** If an AI system is trained with fewer women in leadership roles, it might predominantly recommend men for promotions, perpetuating existing gender disparities (Bender et al., 2021).

- **Curated Data Risk:** Open-source datasets selected for specific outcomes might not represent all the variables needed for project management. For example, using such datasets to predict project timelines could lead to inaccurate predictions, if the data does not include a variety of project types and complexities (Gebru et al., 2018).

- **Algorithmic bias:** The design of AI algorithms can introduce biases, if certain demographic groups are underrepresented in the training data (Mehrabi et al., 2021). This type of bias can lead to decisions that disadvantage specific groups of people, as evidenced in previous studies.
(Barocas et al., 2019). Other types of algorithmic biases include favoring certain technical approaches or interpreting prompts too narrowly or too broadly (Obermeyer et al., 2019). These biases can further affect the decisions and responses generated by AI. Additionally, the biases introduced in the algorithm can be activated or deactivated depending on the user's prompt (Brown et al., 2020).

Examples:

- **Technical approach bias:** An AI algorithm designed to prioritize cost efficiency might consistently recommend cheaper but less effective solutions for project management, disadvantaging projects that require higher initial investments for long-term benefits (Mitchell et al., 2019).

- **Narrow prompt interpretation:** If a project manager asks, "What are the best marketing strategies?" without specifying the industry, the AI might provide generic strategies that are not suitable for a specific industry like technology or healthcare (Shin et al., 2020). This issue is particularly true for open-source AI systems that might have been trained on a broad and generic dataset.

- **Broad prompt interpretation:** Conversely, if a prompt is too broad, such as "How can we improve our business?" the AI tool might generate overly general and less actionable recommendations, missing crucial specifics needed for effective project management (Radford et al., 2019).

- **User bias:** Users' cognitive biases, systematic patterns of deviations from norm or rationality in judgment, can influence how they interact with AI. For instance, users might frame questions in ways that elicit biased responses. However, the use of certain terms by users can continue to elicit responses that neglect other aspects of the project or program. The presentation of the results will be construed by the bounds of the user or team, potentially leaving out some interpretations that need to be discussed (Mehrabi et al., 2021).

Examples:

- **Framing bias:** A project manager might ask, "How can we reduce costs quickly?" This prompt could lead the AI tool to suggest cost-cutting measures that overlook long-term impacts on quality or employee morale (Mehrabi et al., 2021).
- **Term-specific bias:** If a user frequently uses terms like "efficiency" and "speed," the AI tool might prioritize these aspects in its responses, potentially neglecting important factors like sustainability and risk management (Mehrabi et al., 2021).
- **Narrowing dialogue:** A team might ask, "What are the best practices in our industry?" which could lead the AI tool to provide widely accepted practices, while omitting innovative or emerging strategies that could be beneficial (Bender et al., 2021)

Understanding how biases influence AI responses and uses is crucial for optimizing the use of these technologies in project management. Obermeyer et al. (2019) demonstrated that inferences made by algorithms can lead to erroneous results that are close to what might be expected, thus altering the initial objective sought by the project manager. This aspect is particularly critical in project management, where decisions based on inaccurate data can lead to undesirable outcomes (Barocas, Hardt, & Narayanan, 2019).

Examples:

1. **Team members feeling excluded:** Team members might feel left out of the decision process, leading to decreased morale and collaboration.
2. **Risks not being identified:** Risks might not be correctly identified, endangering the project's success.
3. **Inaccurate trend analysis:** Trend analysis might be inaccurate, leading to incorrect forecasts and strategic decisions.
4. **Poor resource allocation:** AI might allocate resources inefficiently, favoring less critical tasks over crucial ones, thus compromising project priorities

Influence of Biases on AI Responses: Biases not only distort AI responses but can also limit its ability to generate innovative and relevant solutions. This issue is especially critical in project management, where decisions based on inaccurate data can lead to undesirable outcomes (Barocas, Hardt, & Narayanan, 2019).

Examples:

1. **Team members feeling left out:** Team members might feel left out of the decision-making process, leading to decreased morale and collaboration.
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3. **Inaccurate trend analysis:** Trend analysis might be inaccurate, leading to incorrect forecasts and strategic decisions.

Inferences Made by Boundary Algorithms: Boundary algorithms can lead to results that seem plausible but are based on erroneous inferences. This phenomenon is particularly problematic when project managers become overly dependent on the AI tool, favoring machine responses over their own and the project and program management team's human cognition. This trust can lead to excessive reliance on AI, neglecting potential errors or biases in the generated responses (Obermeyer et al., 2019).

Examples:

1. **Team dissatisfaction:** One of the biggest issues is team dissatisfaction with their position and a breakdown in communication. If decisions are primarily made by AI, team members might feel excluded from the decision-making process, leading to decreased morale and collaboration.

2. **Excessive reliance on AI:** Project managers who overly rely on AI responses can overlook errors or biases in the generated responses, leading to incorrect decisions that could jeopardize the project's success.

3. **Communication errors:** Over-reliance on AI can lead to reduced communication among team members, as more reliance is placed on AI responses than on dialogue and discussion among team experts.

AI Creativity and Unexpected Responses: Although AI tools lack creativity as defined by human behavior—the ability to make true creative leaps and invent something entirely new not based on existing data—it can still accumulate data through two channels: algorithms and prompts. The algorithm can appear to have creative attributes to human users, generating unexpected solutions based on the provided data. However, some of the AI's tool "creative" responses are actually hallucinations, which are responses that seem plausible but are not grounded in the reality of the project or program for which the user is seeking information.

How Much Can We Rely on AI's Creativity? Imagine managing a complex project. The AI tool has processed available data, as determined by the algorithm: budget, resources, deadlines, and constraints. Concluding that there are no logical solutions to complete the project on time, the AI might determine that the project is destined to fail. In such a situation, a human might find creative solutions outside the box, such as reorganizing resources, negotiating new deadlines, or finding innovative ways to resolve unforeseen issues. These solutions do not directly derive from the data but from the human ability to think creatively and explore non-obvious options.

Currently, AIs, especially those based on language models like GPT-4, excel at combining and optimizing available information but are not yet capable of inventing completely new solutions that are not based on pre-existing data or probabilistic inferences. Studies and articles on the topic, such as "Can AI be truly creative?" (MIT Technology Review) and academic research like Margaret Boden's "The Creative Mind: Myths and Mechanisms", discuss these limitations.

In summary, AI tools excel at combining and optimizing what is already known but lack the capacity for true creative leaps—creating something entirely new that is not based on existing data and inferences. This type of creativity remains a domain where humans surpass machines. Embracing these possibilities allows project managers to successfully navigate project complexities, overcoming limitations and maximizing the opportunities offered by advanced technologies.

Examples:

1. **AI hallucinations:** An AI can generate a seemingly innovative solution that is actually baseless. For instance, an AI might suggest completing a project in less time without realistically considering the necessary resources.
2. **High trust and poor critical evaluation:** Individuals with high trust in AI might accept such solutions without critically evaluating them, risking the implementation of ineffective or unfeasible strategies.
3. **Low trust and deep analysis:** Conversely, those with low trust might completely discard AI-proposed solutions or spend excessive time verifying every detail, slowing down the decision-making process.

Human Reactions to AI Solutions: Human reactions to AI-proposed solutions can vary significantly depending on the level of trust in the system:

- **High trust:** Individuals with high trust in AI tend to accept the proposed solutions and adjust their opinions accordingly. However, this trust can lead to excessive reliance on AI, neglecting potential errors or biases in the generated responses.
- **Low trust:** Individuals with low trust might react by restricting AI use, discarding the data, or deepening the analysis of the proposed solutions. These reactions can lead to further biases and influence how one works with AI.
- **Intermediate reactions:** Most reactions will sit somewhere in-between. The problem is not necessarily how the information is interpreted, but whether there is any validation and verification occurring. In both high and low trust level approaches, the result of such bias can lead to discounting any validation or verification.

Another critical issue is how project managers interpret and react to AI responses. AI algorithms can produce results that seem plausible but are based on erroneous inferences. This phenomenon is particularly problematic when project managers become overly dependent on the AI tool, favoring machine responses over their own or the team's human cognition.

Examples:

1. **High trust without verification:** A project manager might accept a solution proposed by AI without verifying it, leading to the implementation of a strategy that proves ineffective.
2. **Low trust with excessive verification:** Another project manager might spend too much time verifying every detail of the AI-proposed solutions, slowing down the decision-making process.
3. **Intermediate approach:** A project manager, who critically verifies and validates the AI-proposed solutions, balancing trust and skepticism, can enhance the potential effectiveness of the decision-making process.

To address these challenges, project managers must develop a critical understanding of AI's capabilities and limitations. This includes awareness of biases that can influence AI responses and adopting strategies to mitigate these biases. In this context, prompt engineering techniques play a crucial role in improving the quality of AI-generated responses (Brown et al., 2020).

This understanding should consider whether one is using an open-source, contracted, or completely internal AI tool. Each type can come with a variety of bias issues, some of which can escalate over time.

Examples:

1. **Open-source AI:** Open-source AI tools can be curated for specific results, posing a risk to project managers if used for determining schedules or risk identification and treatment strategies. For instance, an open-source model might be trained on data reflecting social biases, perpetuating these biases in the generated responses.

2. **Contracted AI:** AI tools provided by third parties can have embedded biases reflecting the provider's goals or limitations. For example, a contracted AI for risk analysis might favor certain methodologies or perspectives, overlooking other potentially valid options.

3. **Internal AI:** Even internally developed AI tools can introduce biases, especially if the training data reflect the same trends and prejudices as the company culture. For instance, an internal AI tool for resource management might perpetuate existing preferences and practices, limiting innovation and diversity.

Prompt Engineering to Minimize Biases To reduce biases in AI responses, it is crucial to use prompt engineering techniques:

Clarity and Specificity: Clear and specific questions reduce ambiguities and minimize the influence of biases (Brown et al., 2020). Clarity is fundamental to obtaining precise responses from AI. However, clarity must be accompanied by an understanding of the databases that will be accessed so that the data can be validated and verified. Additionally, information technology (IT) projects can be too broad to minimize ambiguities and the influence of biases. Specificity is needed at a level that leaves no doubt about the type of databases to be mined and coalesced into the response.

Examples:

- **Clarity:** Questions like "What are the best practices for risk management in IT projects?" can reduce the chances of misinterpretations, but they need to be even more specific to be truly effective. A better example might be: "What are the best practices for risk management in agile software development projects in mid-sized companies?"

- **Database specificity:** To enable the AI tool to provide precise responses, it is essential to know which databases will be consulted. For example, a specific question might be: "Using the risk management databases from PMI® and Gartner, what are the most effective risk mitigation strategies for agile software development projects?"

- **Data verification:** In addition to asking clear and specific questions, project managers must also verify and validate AI responses. For example, after receiving a response from AI, a project manager could compare the recommendations with industry guidelines or consult with industry experts to ascertain that the information is accurate and relevant.

Appropriate Context: Providing the right context helps AI better understand the user's intent (Radford et al., 2019). However, for an AI tool, the query needs to be more specific to allow for limiting the data to be sourced. For example, a question like "Considering the context of a tech company based in Europe, what marketing strategies are most effective?" provides necessary context but should be further specified.

Examples:

- **Specific tech company:** Instead of a generic question, it might be more useful to ask: "Considering the context of a tech company specializing in business management software based in the European Union, what marketing strategies have been most effective over the past five years?"
- **Additional context details:** Providing specific details about the type of tech company and the timeframe can help AI deliver more relevant responses. For example: "For a tech company specializing in artificial intelligence applied to the healthcare sector, based in Germany, what digital marketing strategies have been most effective from 2018 to 2023?"
- **Limiting data sources:** Specifying data sources can also improve the relevance of responses. An example might be: "Using data from Gartner and Forrester, what marketing strategies have been most effective for European tech companies in the fintech sector between 2017 and 2022?"

Neutrality: Formulating questions neutrally avoids introducing biases (Shin et al., 2020). However, Shin has further elaborated on this topic, highlighting the need for tighter and more specific prompts to further reduce biases. It should be noted that avoidance of biases is the goal, but in some cases, it is hard to identify the bias due to cultural, ethnic, or other influences.

Examples:

1. **Neutral question:** A neutral question like "What are the advantages and disadvantages of implementing remote work?" allows for a balanced and impartial view. However, Shin suggests that prompts should be even more specific to minimize biases. A better example might be: "What are the advantages and disadvantages of implementing remote work in tech companies during the COVID-19 pandemic?"

2. **Team review:** Involving the team in formulating questions helps identify potential biases. For instance, asking, "What are the main challenges and opportunities of remote work in the IT sector?" and having it reviewed by the team can enable greater neutrality and specificity.
3. **Ongoing monitoring:** Neutrality should be an ongoing goal. While reviewing AI responses, the team should monitor and mitigate any emerging biases. For example, if the AI tool tends to emphasize the advantages of remote work without mentioning the disadvantages, the team should adjust the prompts to balance the responses.

Prompt Engineering: Prompt engineering is essential to enable that AI can provide accurate and relevant responses. Prompt engineering techniques guide AI through well-formulated questions, reducing the influence of biases and improving the quality of the generated responses. However, it cannot be guaranteed that all responses will be bias-free. It is the project manager's responsibility to manage these biases and discuss them with their project or program management team. Biases can appear objective when the data used to formulate the response was subjective.

Examples:

1. **PM's Responsibility:** It is the project manager's duty to recognize potential biases and work with the team to mitigate them. For instance, if an AI suggests a strategy based on historical data that might be biased, the project manager should verify and validate such data with the team.
2. **Managing Bias:** During the review phase of AI responses, the team should critically examine the data used to provide that it is representative and free from prejudices. For example, if the data primarily comes from a single source or region, the team should consider including diverse sources to achieve a more balanced view.
3. **Apparent Objectivity:** Biases can seem objective when the data is actually subjective. For instance, a dataset might reflect the opinions of a specific group, giving the impression that the responses are unbiased. The project manager needs to identify these discrepancies and take measures to correct them.

Practical Strategies for Mitigating Biases Project managers can adopt various strategies to recognize and mitigate biases.

Team-Based Approaches: Involve diverse team members in reviewing AI results to identify potential biases. Holstein et al. (2019) suggest that team diversity can help identify and correct biases in machine learning systems.

Examples:

1. **Team diversity:** Involving team members with diverse backgrounds, such as drawing resources from different departments, with various technical and cultural expertise that can lead to greater awareness of potential biases. For instance, a team composed of members with expertise in computer science, project management, and social sciences can offer different perspectives that help identify, reduce introduction, and mitigate biases.
2. **Collaborative review:** A collaborative approach to reviewing AI results can improve the accuracy of responses. For example, organizing periodic workshops where team members discuss and evaluate AI-generated responses can lead to a better understanding of biases and their implications.
3. **Ongoing training:** Providing continuous training to team members on bias recognition and mitigation techniques can enhance the effectiveness of the review process. For example, training courses on how to identify biases in data and algorithms can help team members develop critical skills to address these issues.

Quality Control Practices: Implement rigorous data quality assurance and control measures. Gebru et al. (2018) propose using datasheets for datasets, providing detailed documentation on data collection and usage to improve transparency and reduce biases. Additionally, it is essential to update software and data quality assurance and control processes and procedures to accommodate the evolving field of AI.

Examples:

1. **Datasheets for datasets:** Use datasheets to thoroughly document the data's provenance, collection methodologies, and potential biases. For example, a datasheet might include information on how and where the data were collected, which populations are represented, and which might be underrepresented.
2. **Updating quality control processes:** Regularly update quality control processes to account for new technologies and methodologies. For example, implement specific quality checks for data used in machine learning algorithms, such as verifying the representativeness and completeness of the data.
3. **Ongoing quality control training:** Provide continuous training to team members on best practices for data and software quality assurance. For instance, training courses on how to use quality control tools and how to identify and mitigate biases in data can help maintain high quality standards.
4. **Differences between AI systems:** Consider differences between open-source and proprietary AI systems to better manage biases. Mitchell et al. (2019) discuss how model cards can help document the performance and limitations of machine learning models, facilitating better understanding and management of biases.

Implementing Strategies to Mitigate Biases**:** Implementing these strategies can help project managers mitigate biases in AI systems, improving the reliability and potential effectiveness of the generated responses. However, it is important to note that it is only potential effectiveness because other variables come into play.

Examples:

1. **Diverse team:** Working with a diverse team can lead to greater awareness of potential biases and more inclusive and accurate solutions. For example, involving team members with diverse backgrounds can help identify biases that might otherwise be overlooked.
2. **Rigorous quality control:** Rigorous data quality control practices enable models to be trained on representative and error-free datasets to the extent possible, depending on the users of the AI tool and the level of control the organization can provide. For instance, verifying the completeness and representativeness of the data can reduce the risk of biases in AI responses.

Recognizing and Mitigating Biases to Avoid Unexpected Results

Recognizing Biases:

1. **Training Data Analysis:** Project managers should carefully examine the training data used for AI models. This includes checking for representativeness and completeness. Detailed datasheets can help identify potential biases in the data.
2. **Monitoring Responses:** Continuously monitor AI-generated responses to spot anomalies or unexpected behaviors. Analyzing responses in various contexts can reveal patterns of bias.
3. **Team Involvement:** Engage team members from diverse backgrounds to review AI results. Team diversity is crucial for a critical and impartial review.

Mitigating Biases:

1. **Prompt Engineering:** Use prompt engineering techniques to formulate clear, specific, and neutral questions. This helps reduce bias influence in AI responses. For example, ask balanced questions about the pros and cons of a solution.
2. **Updating Data:** Train AI models on up-to-date and representative data. This oversight action can include integrating new data sources and removing outdated or biased data.
3. **Verification and Validation:** Implement processes to verify and validate AI tool responses. These processes include expert reviews and comparisons with industry guidelines or benchmarks.

4. **Ongoing Training:** Provide continuous training to team members on recognizing and mitigating biases in data and algorithms. This approach can include courses on the latest AI techniques and methodologies.
5. **Transparency Tools:** Use tools and practices that enhance AI model transparency, such as "model cards" and "datasheets for datasets." These tools provide clear and detailed documentation on model performance and limitations, facilitating better understanding and management of biases.

Practical Example: A project manager using an AI system to evaluate employee performance can follow these steps:

1. **Analyze training data** to provide that it is a balanced representation of employee populations.
2. **Monitor AI responses** to detect any discriminatory trends.
3. **Engage a diverse team** to review AI-generated performance evaluations.
4. **Use prompt engineering** to formulate neutral questions like "What are this employee's strengths and areas for improvement?" instead of biased questions.
5. **Regularly update data** to reflect current company and labor market dynamics.
6. **Verify and validate** AI to provide proper data cultivation for solution sets, and if possible, the data being used, by comparing them to human feedback and company guidelines.
7. **Provide ongoing training** to the team on identifying and mitigating biases in performance evaluations.

By implementing these strategies, project managers should be able to recognize and mitigate biases in AI systems, reducing the risk of unexpected and potentially harmful results.

Exploring How Biases Are Incorporated into AI Processes Exploring the multiple ways biases can be incorporated into AI tools' processes is crucial for fully understanding the problem's scope. Biases can be introduced at various stages, from data collection to feature selection, algorithm design, and even in interpreting results (Barocas, Hardt, & Narayanan, 2019). Understanding these dynamics helps project and program managers better identify critical points where biases can emerge, assist with identification, and adopt preventive measures.

Focusing on One or Two Specific Aspects of Bias Focusing on one or two specific aspects of bias allows for a more in-depth and targeted analysis. For example, project managers might primarily focus on biases introduced during data collection and algorithmic biases. This focused approach allows for the development of more effective and specific mitigation strategies for those particular contexts.

Defining a Path to Becoming Informed and Cautious AI Users To become informed and cautious AI users, project managers should follow a structured path that includes continuous education, adopting best practices for data management, and using quality control tools. Part of this path also involves collaborating with data experts and AI developers to provide models are transparent, fair, and reliable. Creating an ethical framework and adopting data governance practices are essential to maintaining the integrity and reliability of AI solutions.

Practical Examples for Project Management For example, a project manager might use a risk prediction model that, due to biases in historical data, underestimates the risks associated with certain types of projects. Another example could be the use of resource optimization algorithms that unknowingly favor certain workgroups due to biases in past performance data. These concrete examples can help project managers better understand the practical implications of biases and develop strategies to address them.

Conclusion In summary, biases in an AI tool and project management practices present significant challenges, but most can be identified, and strategies developed to minimize impacts. Understanding and addressing these biases through prompt engineering techniques, involving diverse teams, and rigorous quality control practices enable project managers to effectively leverage AI while mitigating its risks. By adopting these strategies, project managers can make more informed and objective decisions, improving project outcomes.

Glossary of Terms

1. **Boundary algorithms:** Algorithms that work at the decision limits, often used to distinguish between different categories or classes in machine learning models.
2. **Algorithmic bias:** Prejudices introduced during the design or implementation of algorithms, leading to distorted or unfair decisions.
3. **Prompt engineering:** Technique used to formulate questions or commands precisely and clearly to obtain accurate responses from AI models.
4. **Language models:** AI systems trained to understand and generate human text, like GPT-3, which use large amounts of data to learn language.
5. **Abductive inferences:** Process of forming hypotheses based on incomplete observations, often used by AI models to make deductions.
6. **Datasheets for datasets:** Documents that describe in detail the collection and use of data in datasets, improving transparency and reducing biases.

7. **Model cards:** Documents that provide information on the performance and limitations of machine learning models, helping to better understand and manage biases.

8. **Technological bias:** Tendency to place excessive trust in technology-provided solutions without questioning them.

9. **Inferences made by algorithms:** Deductions and conclusions generated by AI algorithms based on input data, which can be influenced by biases.

10. **Data bias:** Prejudices present in the data used to train AI models, leading to distorted responses.

11. **User cognitive biases:** Mental prejudices and tendencies that influence how users formulate questions and interpret AI-provided responses.

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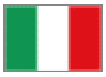
About the Authors

Ivano di Filippo

Rome, Italy



Applied Cognitive Neuroscience Scientist specializing in Project Management and AI
LinkedIn Profile | Official Website | Publications | Link to the book

Ivano di Filippo is a distinguished scientist in Applied Cognitive Neuroscience, focusing on project management and artificial intelligence. He currently leads the Cognitive Readiness Research Program, which is dedicated to advancing the mental preparation of leaders. From 2017 to 2019, Ivano served on the Board of Directors at the Italian Institute of Project Management (ISIPM), where he also holds certification as a Project Manager.

Educated in medicine at La Sapienza University of Rome, Ivano furthered his technical skills in computer science, working for ten years as a professional IT and Web programmer. His diverse expertise is enriched by over 30 years of studying and practicing Zen, integrating oriental disciplines into his professional and personal life.

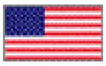
In 2011, Ivano joined forces with Prof. Dr. Russell Archibald and Dr. Daniele Di Filippo in the international research program on Cognitive Readiness, eventually succeeding Dr. Archibald as the Program Director at his request.

In November 2022, he was appointed the Scientific Referent at ISIPM, continuing to impact the field with his innovative approach to integrating neuroscience into project management practices.

He is the co-author of the book "Cognitive Readiness in Project Teams - Reducing Project Complexity and Increasing Success in Project Management". He can be contacted at

Dr. Josh Ramirez

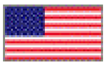
Washington, USA



Dr. Josh Ramirez, PMP, NPPQ, is CEO of the Institute for Neuro & Behavioral Project Management, which he founded with Dr. Jodi Wilson. Josh is also co-author of the NeuralPlan (www.neural-plan.com) NPPQ master planner certification with Dr. Shari De Baets from Belgium, and he is an adjunct professor of project management, with experience that includes project management and project controls, including work at several national laboratories and other projects throughout the U.S. Department of Energy (DOE) complex. He has authored best practices for the DOE Energy Facilities Contractors Group and wrote for other project management periodicals. His doctoral dissertation is titled Toward a Theory of Behavioral Project Management. You can view an introduction to Josh and his colleagues' work in Behavioral Project Management at https://youtu.be/miqbagN_4dQ. The future of project management is designing PM methodologies around the beings that predict and deliver projects: humans. You can also listen to some of the podcasts Josh and his colleagues have been featured on, here: Behavioral PM: the Freakonomics Approach to Project Delivery with Dr. Josh Ramirez - https://pmhappyhour.com/ep077/; Neuroscience in Project Management - https://www.pmi.org/chapters/wdc/pmi-resources/pm-podcasts/pm-point-of-view-69; Tips from Behavioral Science - https://www.pmi.org/chapters/wdc/pmi-resources/pm-podcasts/pm-point-of-view-95.

Darrell Mesa

California, USA



Darrell Mesa, a Senior Program Planner / Scheduler and a dynamic intrapreneur, with extensive expertise in project management, including program planning, scheduling, and risk management. As a certified Project Management Professional (PMP), he has a demonstrated history of steering large-scale projects to success by applying industry best practices, with special proficiency in Earned Value Management (EVM), Critical Path Schedule Management, and Work Breakdown Structure. His role as a Microsoft

Project Practitioner at Denver Corporate Search showcases his ability to develop and update intricate MS Project schedules, adhering to stringent government regulations.

Darrell's professional journey is marked by significant roles that have allowed him to leverage his skills effectively. At Projitz LLC, as a Senior Program Planner / Scheduler, he enhanced project efficiency through meticulous application of Work Breakdown Structure and Critical Path Analysis. As a Senior Integrated Master Scheduler at Highbury Defense Group, he made notable improvements in program efficiencies through the execution of Integrated Master Schedules and the integration of Earned Schedule methodologies. A key achievement in his career was the development of 89 Project E-cademy training courses, which increased team productivity by 10%. In his capacity as a Learning Management Administrator, he demonstrated dedication to knowledge dissemination, using WordPress Tutor LMS to bolster team skills in Project Scheduling using Microsoft Project Professional and Project Web App.

In addition to his corporate roles, he is the founder of Influence IPM LLC, a business focused on Integrated Project Management, where he leverages his vast experience to provide cutting-edge project management solutions. More about his entrepreneurial venture can be found at influenceipm.com. Beyond traditional project management, he is also an active AI Influencer through his YouTube channel (Restless Minds), where he creates and shares content on AI advancements, fostering a community of tech enthusiasts and professionals keen on the latest in artificial intelligence. Based in Murrieta, California, he is keen on connecting with like-minded professionals and can be reached via email at darrell.mesa@pm-ss.org or through LinkedIn at https://linkedin.com/in/darrell-mesa-pmp-csm-4bbb8955.

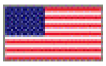
Claudia Alcelay

Madrid, Spain

Claudia Alcelay, Product Manager, AI | PMP®, PMIACP, CSPO®, SAFe 5 is an experienced project manager specializing in AI with a deep background in innovation, particularly in driving the evolution of the EdTech sector. She has served for the European Commission and various ministries in Spain, Egypt, and France. She currently works as a Product Manager for AI with a focus on developing innovative solutions to enhance training portfolios. Additionally, her professional journey involves leveraging a knowledge-based approach in data-centric AI models. She is an active community member, sharing her findings in her weekly newsletter, on LinkedIn, "My AI Reading List," and also serving as a panelist for MIT Technology Review and participating in the Advisory Council for Harvard Business Review (HBR). She can be contacted at caceley@gmail.com

Rebecca (Becky) Winston

Idaho, USA



Rebecca (Becky) Winston, Esq., JD, PMI Fellow, is a former Chair of the board of the Project Management Institute (PMI®). Becky has over 30 years of experience in program and project management, primarily on programs funded by the US government or their contractors.

Active in PMI since 1993, Rebecca Winston helped pioneer PMI's Specific Interest Groups (SIGs) in the nineties, including the Project Earth and Government SIGs, and was a founder and first co-chair of the Women in Project Management SIG. She served two terms on the PMI board of directors as director at large, Secretary Treasurer, Vice Chair (for two years), and Chair (2002). She was elected a PMI Fellow in 2005. She is also a member of the American Bar Association and the Association of Female Executives in the United States. She currently is the Executive Vice President of the College of Performance Management and the lead for their ISO standards committee given her 25 plus years of ISO experience.

She has served as an advisor to organizations such as the National Nuclear Security Administration (USA), U.S. Department of Energy (DOE) and the U.S. Department of Homeland Security (DHS) on topics ranging from Program and Project Management to project reviews, risk management, vulnerability assessments, software development and artificial intelligence. She served on the Air Force Studies Board for six years and serves the Intelligence Science Technology Engineering Group for the National Academies of Science, Engineering, and Medicine, as well as actively serving on many studies for the National Research Council. She can be contacted at rebeccawinston@yahoo.com