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HERSHEY M. CATIMBANG

ENHANCING AI ADOPTION IN THE R&D WORKFORCE TOWARD PRODUCTIVITY GAINS OF AN INDUSTRIAL TECHNOLOGY ORGANIZATION

Special Problem Adviser:

DIGNA O. MANZANILLA, Ph. D.
Faculty of Management and Development Studies

28 April 2026

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DIGNA O. MANZANILLA, Ph. D.
Faculty-in-Charge, R&DM 298 (Special Problem)

April 28, 2026
Date

LEO MENDEL D. ROSARIO, Ph. D.
Program Chair

April 28, 2026
Date

FINAFLOR F. TAYLAN, DProfSt
Dean
Faculty of Management and Development Studies

April 28, 2026
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DECLARATION

This is to certify that:

I. The special problem comprises only my original work towards the MRDM, except where indicated in the Preface

II. Due acknowledgment has been made in the text to all other material used

III. The special problem is fewer than 25,000 words in length, exclusive of tables, maps, bibliographies, and appendices.

Hershey M. Catimbang

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ABSTRACT

AI's potential is recognized as an enabler in delivering time to market products faster, supporting market growth and expansion, and protecting the bottom line through improvements in productivity and efficiency; as well as harnessing innovation in order to maintain market leadership. With many industrial technology companies seeing the AI revolution, understanding the many facets of Research and Development (R&D) workforce to achieve accelerated AI adoption is critical, amidst this rapidly evolving technology.

This study employed qualitative research methods, drawing on structured questionnaires, follow up interviews and review of internal documentation identifying issues encountered related to AI adoption and defining R&D organizational factors that affect its results. With a case study approach, data analysis involved four (4) key themes: (1) organizational structure, (2) employee behavior and employee engagement, (3) AI literacy and (4) organizational policies and ethical considerations.

It defined a framework for enhanced AI adoption of an R&D system in a technology development organization, by identifying and addressing the gaps in its organizational structure and workforce composition. Focusing on the industrial technology organization reviewed, this study provided a timely and relevant approach to adopt AI in the workplace to positively impact the R&D goals of faster time to market development through productivity improvements. The findings derived in this study led to the four recommendations to enhance AI adoption, including: (1) defining a formal AI organizational structure to drive and coordinate AI projects; (2) creating AI-focused

employee engagement programs; (3) investing in AI proficiency role-based trainings and (4) establishing an adaptive AI governance.

I. RATIONALE

Organizations in high technology industries are competing to be front runners in leveraging AI in their R&D workplace to generate products of high precision and services with competitive edge. This has been a strategic imperative among organizations to stay relevant to the growing complexity and shifts in customers' requirements and to gain faster and more efficient R&D operations. With the advent of AI and its rapid pace, the need for its adoption, from Agentic AI to Generative AI, creates a higher mandate to apply significant investments in all possible R&D areas. These include fulfilling engineering tasks, such as, design and development activities. Reflecting on the importance of AI at work, CEO of Alphabet, Sundar Pichai during the World Economic Forum in 2018 said, *"I've always thought AI as the most profound technology humanity is working on … more profound than fire or electricity or anything that we've done in the past."* Petroff (2018) highlights the necessity to prioritize AI adoption in an organization.

Tien et al. (2025), noted the use of AI in R&D can increase productivity by 30% for repetitive tasks, while in product development, it can decrease the cycle time on different phases from ideation up to full production release. However, despite these expected results, Shokran et al. (2025) indicated that many companies are still encountering challenges to scale their AI programs to fully realize their organizational goals. The human aspect is identified to be a critical factor in sustaining AI strategies.

Singla et al. (2025) described a jump in the use of AI in global organization with 78% of surveyed companies claiming they are already using AI on at least one of their business functions. Product development and software engineering rank, second and third, respectively, on GenAI (generative artificial intelligence) use among different functions. About 51% of organizations observed revenue increases on product development and 57% on software engineering with AI integration. With higher cost reduction and increased revenue gains through AI, Bellefonds et al. (2024), highlighted that an organization with slower AI adoption will put itself at risk of maintaining its market advantage since competitors will be able to further lower their operational cost and enable faster time to market. In the same study, they have noted that 35% of business units reported an increase in revenue in the first half of 2024 growing to 51% after six months, showing a compounding gap between companies who use AI now to those who decided to delay or scale down its adoption.

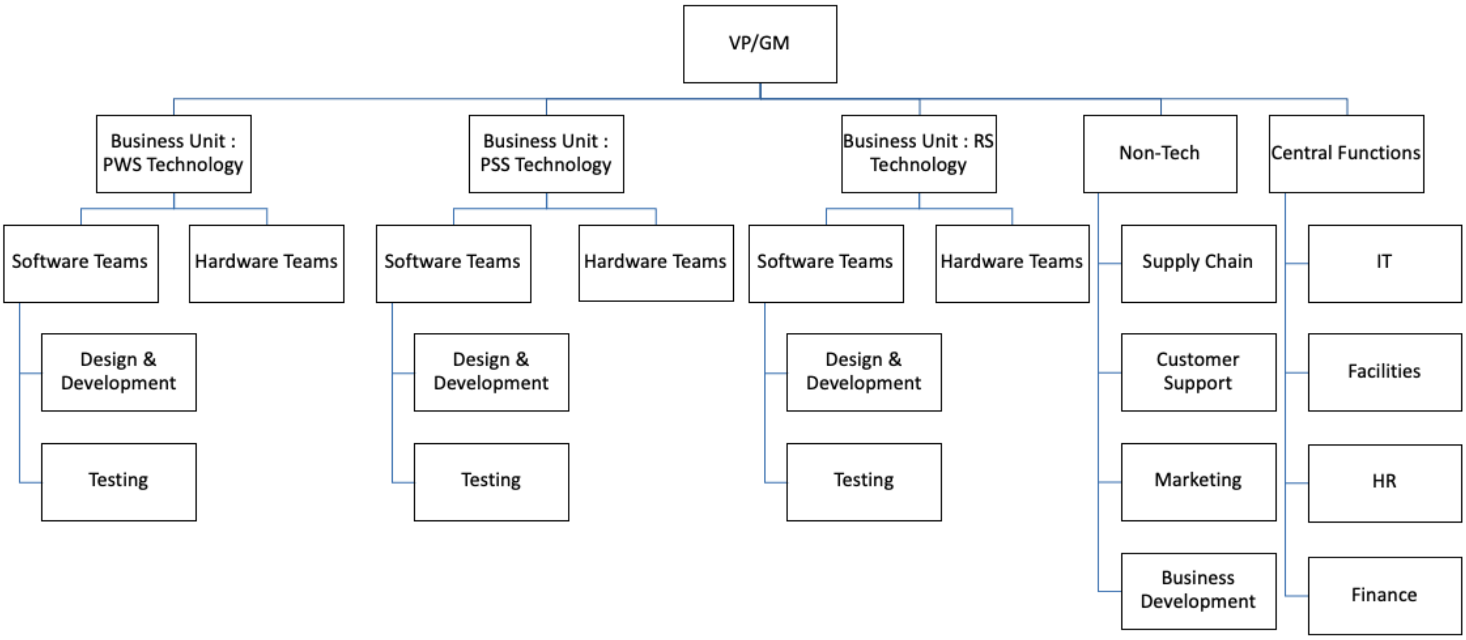
In a similar manner, postponing the full AI adoption in an industrial technology organization could result in losing market dominance. If competitors will be able to do more with less by developing and testing products faster, this will result in accelerated production release, putting the organization with lower AI integration at a disadvantage. It is highly important to apply approaches to accelerate AI use at work to maintain its technology leverage.

Lower AI adoption in technology organizations is observed to be contributed by factors like ineffective organizational structures and policies, gaps on employees' skills and competencies and employee behaviors. Singla et al. (2025) stated that many organizations automatically refer to their Information Technology department for AI ownership; however, this approach is repeatedly unsuccessful. Challapally et al. (2025) noted that the top cause of failure in piloting AI is employees' unwillingness to try the corporate defined tools. Mayer et al. (2025) indicated that employees have identified training as the top factor to enable AI adoption. However, most of them cited that they have received insufficient training. Despite employee readiness to adopt, the absence of adequate learning programs and appropriate employee empowerment delay scaling up of AI use.

II. PROBLEM STATEMENT

This study focuses on enhancing AI adoption by the R&D employees to better achieve the productivity goals of an industrial organization. Typically, in this case organization, the R&D units are structured and operating based on business units (BUs). As shown in Figure 2.1 functional organizational chart, business units include Power and Water Solutions (PWS) who is responsible for technology solutions for power, water, and waste water treatment plants. Process Systems and Solutions (PSS) takes on solutions and applications for process automation for oil and pharmaceutical industries. The Reliability Solutions (RS) captures the asset health monitoring and predictive systems.

Figure 2.1. Functional organizational chart for technology development.



Prioritized AI projects per BU differ from one another. For example, in one business unit, productivity improvement is measured by lowering the time spent to generate test cases for software testing. With the use of AI, a software tester can produce the same number of software test case counts in less time, from 10 days to

10 minutes. In another BU, the focus of productivity improvement is defined by an increase in the number of codes written through automated code generation. A normalized productivity gain measurement is translated to being able to produce more. This will be equivalent to the number of R&D output from the input provided which is either in full time equivalent (FTE) or hours worked. For example, in the testing activity that requires creation of test cases, current productivity, when done manually, is at 34 test cases created per 80 hours or 0.43 test case per hour. In comparison, for AI augmented work, this will be 34 test cases per 0.17 hour or 200 test cases per hour. Here, the productivity jumped from 0.43 to 200 which is the desired result of the organization as it performed its R&D tasks and activities.

Leveraging best practices between BUs, operating separately but with the same functions, is an observed issue since scaling up and maximizing the use of AI with other units is not automatically and systematically applied. This is the case for AI adoption since each business unit performs their software and hardware development activities and fulfills their functional objectives separately.

With a top-level mandate to use AI at work and an overall defined target of cost reduction through productivity improvement, AI is adopted where it is seen to be most valuable. The emphasis of implementation is driven by a bottom-up approach. Employees are empowered to experiment and apply AI where they see fit and appropriate. However, this approach is fragmented and lacks proper coordination between units. Although quick wins are observed and employees are implementing practical use to solve their problems, inconsistent practices exist on how to use AI from one business unit to another.

AI usage in the organization is governed by policies, approval process, constraints, ethical and responsible use, communicated through employee cascades, email notifications and policies publication. Given this scenario, R&D employees who worked on AI projects continued to have varying levels of AI involvement. For example, a team of 20 employees that includes software developers, software testers, hardware engineers, cybersecurity manager and development managers formed a local AI committee that meets every week to discuss site level AI projects, track their progress and highlight impediments and support needed. These employees expressed and demonstrated full interest in adopting AI at work and are championing the AI use within their own business unit and function. The rest of the employees have different degrees of willingness, skills, interest and initiative to apply AI in their activities. Inability to address these issues will lead to lost opportunities to leverage the benefits that can be achieved if AI is applied across the whole organization thereby maximizing productivity gains across all common functions and activities.

Overall, this study aims to answer: How can an industrial technology organization, under this case study, enhance the AI adoption of its employees to improve productivity?

Research Questions

This study will seek to address the following research questions based on the perspective of the selected industrial technology organization:

- What are the challenges and issues in the current application of AI in the R&D workplace, related to the following aspects (1) organizational structure, (2) employee behavior and employee engagement, (3) AI literacy, (4) organizational policies and ethical considerations in the adoption of AI?

- What R&D workforce approaches on the aspect of organizational structure, employee behavior and employee engagement and AI literacy should the industrial technology organization apply to achieve higher AI adoption?
- What are the benefits of enhancing AI adoption into the R&D working environment?
- What organizational policies and ethical consideration should the industrial technology organization apply to achieve higher AI adoption?

III. OBJECTIVES OF THE STUDY

With the rapid evolution of AI and its observed potential to transform a business, there is now an imperative to accelerate AI adoption and embed it into technology development processes of the case study organization. The overall goal of this study is to determine how to enhance AI adoption in the workforce of an industrial technology organization, in order to improve its productivity gains. The following are the specific objectives of this study:

1. Determine the challenges and issues in the current application of AI in the R&D workplace, related to the following aspects: (1) organizational structure, (2) employee behavior and employee engagement, (3) AI literacy, (4) organizational policies and ethical consideration in the AI adoption.
2. Determine how the AI adoption in the Design and Development phase of the New Product Development (NPD) process impacts productivity gains in software and hardware development outputs.
3. Evaluate the AI readiness of the organizational structure of the R&D units under the software and hardware teams.
4. Assess the effect of employee behavior and employee engagement within the software and hardware teams on the enhanced use of AI in their workplace.
5. Identify AI literacy requirements to increase productivity in hardware and software development activities.
6. Determine how the challenges in the existing organizational policies and ethical consideration can be addressed to achieve higher AI adoption in the R&D workforce.

7. Develop a framework, based on the findings of the study, to enhance AI adoption in the R&D workforce for higher productivity of the design and development activities.

IV. R&D MANAGEMENT FRAMING

This research contributes to a better understanding of how the organizational and employee related factors can impact the AI journey of an R&D organization. Shokran et al. (2025) shared that organizations that effectively use AI allow their businesses to optimize their resources. They added that within the R&D sector, the software developers and engineers are observed to have higher initiative to upskill and that the organization in the technological sector leads in deploying more AI training efforts. Software developers are also observed to have higher motivation to use AI due to available programming tools and automation that lessen their time to do coding. With AI adoption and its ability to speed up day to day operation, organizations can expect to decrease development time and lower down resource expenses which will result in higher profit helping them to sustain their market position.

AI similar to its other predecessor technology will also demand organizational changes to drive favorable benefits. Rudko et al. (2021) highlighted how organizational fit with AI is an important factor to sustain the competitive benefit that can be gained by this technology, thus understanding if changes applied to adoption of AI will trigger resistance or will stall its growth, requires attention. They also supported the individual first approach in change management, valuing the importance of the workforce and taking care of the psychological aspect. They noted that redesigning activities based on how the type of work evolves needs to be done such that it will also drive favorable and positive behavior among employees. This includes equipping employees with necessary skills to better position them on how to work with AI. Benlian and Pinski (2025) shared AI literacy as a key contributor in progressing the organization's transformation. They have highlighted that AI literacy is not a "one-size-fits-all" and has to adapt based on the distinct learning needs per type of role, function or activity. They presented three dimensions of AI literacy including conceptual literacy, ethical literacy and practical literacy, offering a more holistic and systematic approach to fulfill gaps seen from its workforce. Additionally, the governance for AI as a technology, tool and application in producing R&D output becomes necessary to evolve from its traditional governance framework to a more up to date approach. Lin (2025) shared that the current AI governance structures show gaps in enabling faster innovation due to constraints introduced by risk mitigation effort particularly for legacy governance processes. This necessitates attention in evolving the organizational AI governance to support the continued enhancement of AI adoption of the organization.

This study is significant to the industrial technology organization being reviewed in support of its strategic AI transformation. With the growing complexity of requirements from their customers and the demand to release best valued products and systems faster and more frequently, the R&D activities are required to be done with the optimal use of resources. With AI-skilled employees, these internal organizational needs will be fulfilled through effective AI adoption. While their customer needs continue to evolve, the organization will have to keep advancing on its design and development activities by automating their repetitive tasks accomplished with the use of AI. The result of this study will benefit the R&D managers to arrive at specific actions to address the identified challenges and gaps on AI adoption. This in turn, can help the organization achieve its target productivity gains from R&D activities. Applying these actions within the organization, will produce positive customer impact by having faster turnaround time on feature requests, improvement on product releases that are more robust, stable and future-ready. These will consequently impact the ability of the

R&D organization to establish a stronger trust and relationship with customers because of the predictability and accountability gained.

V. CONTEXTUALIZATION OF THE R&D ORGANIZATION ENVIRONMENT

Industrial technology organizations are composed of highly technical employees with diverse engineering backgrounds. Many have been active in their own innovation journey, applying new technologies and incorporating them in their R&D organization. However, the accelerated nature of AI technologies requires a more differentiated approach. For this study, a thorough review of related literature was done to determine the common themes defining the framework for enhancing AI adoption toward higher productivity gains in an industrial technology organization.

Review of Literature

Organizational Structure and Model Fit to Achieve Adaptive and AI-Oriented R&D Employees

Singla et al. (2025) explained the trend of AI adoption between centralized, decentralized or hybrid models for organizational structure and deployment on AI. When adopting AI solutions, more than half uses hybrid wherein some employees are centralized and some are distributed across functions. Kesby (2025) stated that for an AI-powered organization, its structure has to be shaped beyond the traditional top-down approach to allow for higher flexibility and faster innovation. Rudko et al. (2021) noted that the decentralized approach is the leading trend highlighting that too much hierarchy limits adaptability and is counter-productive for a more agile type of technology. A flat hierarchy compared to tall hierarchy achieve results faster when decisions are done by those doing the actual work. Majority has a dedicated team to drive AI adoption. Some teams are using decentralized approach by doing their work on their own instead of relying with a command-and-control strategy. Understanding which organizational model will fit best based on the goals and objectives that an organization would like to achieve will need to be defined accordingly.

High Employee Engagement and Behavior as Enabler for Higher AI Adoption

Highly engaged employees are individuals that would like to contribute positively to the organization because they believe their work is valuable and their contributions are being recognized. Introducing new strategies in an R&D organization such as the use of AI falls within a type of organizational change, and Swarnalatha and Prasanna (2013) noted that employee engagement is a key factor for its success. Singla et al. (2025) suggested that best practices involve an established mechanism to incentivize employees for higher AI adoption. The ability to sustain this engagement as the team explores AI in their work will be a key factor if its adoption that will expand beyond the initial team.

In Harvard Business Review (2023), a powerful message from Karim Lakhani indicated how those who do not use AI will be replaced by those who do. Singla et al. (2025) shared that for software engineering, almost one fourth of the total number of companies included in the survey indicated a decrease in the need for employees in the next three years due to the use of Generative AI. It is therefore a common perception how AI will impact someone's work. Kesby (2025) highlighted that employee motivations are initiated by either favorable or unfavorable emotions about AI. It may lead to a negative response or anxiety towards AI's use or a positive response or excitement to try new things taking more ownership of what's to come. He added that the absence of employee buy-in will put upfront challenges on successful AI adoption. It is therefore important to understand these employee behaviors and how to handle push backs and objections to drive enhanced AI adoption.

Technical Competencies and Essentials Skills for Effective AI Use

Mayer et al. (2025) noted how almost half of leaders surveyed has specified skills gaps to be a contributor in successful AI adoption. They added that upskilling of their current employees using tailored trainings appropriate for their roles, is crucial for scaling up AI use. This means higher adoption requires that the R&D employees should know how to use an AI application effectively. These will require matching of competencies and skills or AI literacy of R&D employees to increase their confidence and effectiveness on its use. In software and hardware development functions, as part of the R&D units of the industrial technology organizations, the R&D employees have existing technology savvy competency in the usage of tools and automation to increase throughput during development. The AI applications vary from software coding, software and hardware debugging, design reviews and product testing.

Kesby (2025) described the practical use of AI as Amplified Intelligence combining human intuition and AI to accomplish an outcome. However, real use cases and current AI capabilities will dictate the basic technical know-how required for a specific software developer or hardware developer role. Kesby (2025) also described an AI capabilities spectrum. In this spectrum, the software and hardware development activities have applications that generally have high effectivity. Highly reliable applications involve data extraction from structured formats and capturing basic responses through natural language which are 90% effective. These can be performed through AI prompts that can suggest a software code to a desired application.

Moderately reliable applications have at least 70% effectiveness. Examples of these are document generation from structured inputs which are valuable for hardware developers and can use AI to create functional specifications by allowing it to ingest the hardware drawings. Due to the differences in the effectiveness of different development use cases, structured and tailored training will play a role in defining selections that match the need per role.

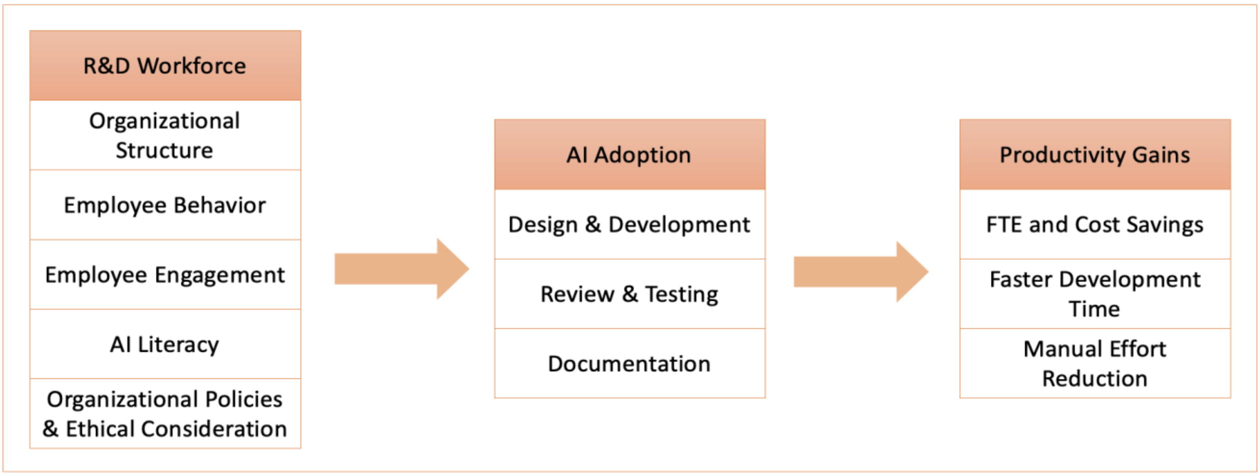
Organizational Policies and Impacts on AI Adoption

Dasgupta and Wendler (2019) defined the top-down approach in AI adoption which allows wider implementation for organizational decisions on AI. These include AI principles to implement, ethical and responsible use of AI and general governance. Mayer et al. (2025) noted the importance of setting policies and processes for monitoring of AI tools to manage risks and address visibility issues across the whole organization. With a standardized way of doing things that is favorable for consistency in adoption, this approach will be more complex and expensive when used in a large organization. Meanwhile, the bottom-up approach provides low risk when it comes to creating disruption in the operation while gaining immediate impact to the employees. However, the acceleration of adoption is slower, prone to working in silos, with productivity gains from different business units or functions not standardized or leveraged. Being able to balance what policies should be done, top-down or bottom-up, or a hybrid between the two, will be critical in balancing speed and complexity of the organizational approach.

Conceptual Framework

A conceptual framework on enhanced AI adoption to achieve productivity goals is presented in Figure 5.1.

Figure 5.1. Conceptual framework of the study.



This framework provides useful approaches to R&D managers and key stakeholders who would like to accelerate the AI adoption within their R&D organizations to achieve tangible outcomes. Each factor is identified as organizational and workforce development enabler to drive higher AI adoption toward achieving productivity gains. These will provide insights on how such factors can influence employees' use of AI in the workplace. Employee behaviors such as openness to change and adaptability will translate to personal initiative to experiment and participate more in AI projects. Opposite behaviors will be indicative for R&D managers of the need to reinforce feedback collection to identify the root cause of hindrance. Employee engagement is affected by the motivation level of employees to either be an AI pioneer or a laggard. The presence of low engagement on AI activities will signal R&D managers to reinforce accountability and ownership on AI projects and elevate employee empowerment during formal cascades and AI incentive related programs. An organizational structure designed for expedient decision-making will enable R&D managers to revisit roles, responsibilities, and assignment in order to identify the appropriate approaches for the technology organization constrained by BU directives. Priority will be given to the review of organizational policies that are hindering immediate adoption of AI use at work. This will provide insights on what policy changes need review and approval and will then have to be prioritized and addressed. Finally, AI literacy will provide insights if the employee's low adoption is due to lower technical and soft skills proficiency. R&D managers will be able to look at these gaps enabling them to propose a more tailored training program based on employee roles and capabilities.

Shokran et al. (2025) concluded that better operational efficiency and improved financial results will be the bottom-line result of AI adoption. These will be achieved through higher productivity gains from the adoption of AI in the different R&D activities. Within the R&D activities, AI is being applied in various areas including design and development, review and testing and documentation. In design and development, AI-related activities include AI-supported software coding, with scripts or logics that are being checked, refined and updated by an engineer prior usage. This helps in faster iteration of design ideas and exploration enablement of multiple options quickly without starting from a blank slate. In review and testing, these include activities such as AI-assisted test case generation, automation of regression testing and repetitive validation tasks, to help increase the coverage and consistency of testing in a shorter amount of time. AI tool also functions as a secondary reviewer. This feature allows the engineers to capture any potential issues and identify suggestions and improvements that can be applied on the design. The engineers validate these findings which allowed for a more thorough checks improving the quality of design and development output. Finally, in documentation, AI enables generation of initial draft of technical documentations, reports and summaries that gets finalized after engineer's review. Another application of AI in documentation is summarizing technical documentations needed in the design, standardizing the document output by creating secondary checks for consistency, structure, terminology, and clarity.

Productivity gains which pertain to more output, higher quality or faster completion of R&D work using the same resource count are observed through full time employee (FTE) or cost savings, faster development time and manual effort reduction. Full time employee count is a generalized metric used to define an effort to complete an R&D task. Savings is calculated when comparing effort used with and without AI assistance. Given that the general expense for an R&D project is driven by development cost through hours spent by the engineers, reported time savings when AI replaces the manual and routine work translate to productivity gain. Faster development time pertains to shortening the design, development and testing cycles not by elimination of steps or testing coverage but by utilizing design and test AI generated R&D output enabling faster feedback loop during development. The shortened cycle requires less development time, resulting in productivity gains as additional capacity gets allocated for design iteration without adding employees. Finally, manual effort reduction refers to less time used on repetitive and administrative tasks by moving activity from manual to automated. As emphasized, this output, even if performed automatically, continues to require engineer's review and validation although the cognitive load was already reduced.

VI. METHODOLOGY

Locale of the Study

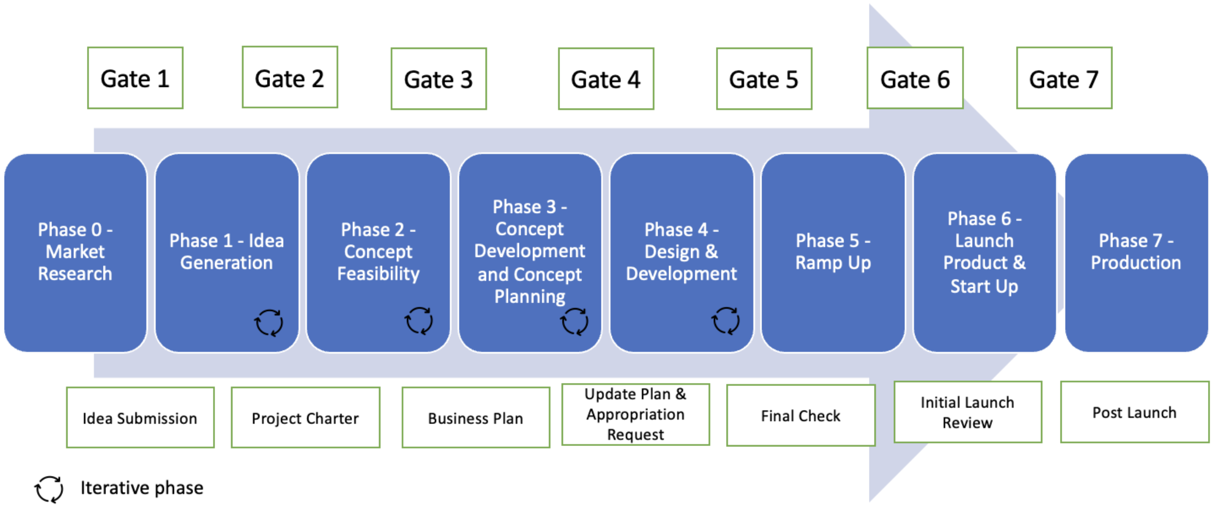
The study focuses on an industrial technology organization involved in various stages of product development, from conceptualization, design and development and delivery of products and developing systems and solutions, to automating plant processes for various customers of a wide range of applications. These systems and software solutions enable process automations for energy, water and waste water treatment plants, oil and gas, chemical and pharmaceuticals plants. The development of control systems and software platforms require huge investment in engineering hours to complete a successful release. With AI use, these engineering hours are decreased allowing developers to have more frequent releases. For example, software development time is decreased by writing software code faster through predictive coding, by automating software testing instead of executing them manually and by decreasing time to review codes through AI based code reviewers. In hardware development, engineering hours are saved by decreasing time to review the design using AI based schematic and layout design reviewer.

Research Design

This uses a qualitative case study approach to determine how to improve the R&D employees' AI adoption in an industrial technology organization. It reviews the current gaps and challenges in these areas to arrive at a framework that enhances AI adoption to have higher productivity gains.

This R&D organization is using the New Product Development or NPD process which has seven (7) phases from Phase 0 or Market Research up to Phase 7 or the Production Phase. In Figure 6.1, Phases 1 to 4 employ an iterative approach. In relation to assessing R&D productivity using AI, it will be centered on activities performed in Phase 4 or Design and Development where the detailed design, development and systems integration are completed.

Figure 6.1. New product development process.



Software design and development activities under Phase 4 includes code generation, code reviews, test plan and test cases creation, unit testing, system integration testing, finding resolution and technical document. Hardware design and development activities under Phase 4 includes schematic capture, printed circuit board layout, mechanical design, bill of material generation, design reviews, test plan creation, prototype testing, troubleshooting, report preparation and technical documentation.

The productivity gains are determined by the outcome of AI adoption. Productivity gains are observable through FTE and cost savings, faster development time and manual effort reduction. For specific activities under the Design and Development phase, examples of these gains include higher number of test cases executed with the use of AI test monitoring, more software issues resolved using AI fix recommendations and faster code generation. These will be evaluated against different contributing factors that include organizational structure, policies and AI ethical use and employee aspects that cover employee behavior, capabilities and engagement.

Looking at the organizational structure, the study assesses the BU-specific approach and the localized AI committee that is championing the AI site level effort in terms of the productivity gains achieved for AI projects against set goals. Each BU has its own way of enforcing AI adoption based on BU management directives. Some BUs are structured to have loose direct reporting requirements to their management team about their AI goals and targets, while other BUs are more explicit due to this requirement. This study evaluates these structures in terms of variability between achieving defined goals and benefits realized. It looks into the level of collaboration between business units and review the result of a more bottom-up approach during implementation, given that policies and governance are already deployed based on the current top-down approach.

Understanding the employee capabilities covers knowledge strengths and weaknesses and the study evaluates required competencies against the design and development activities of the R&D employees in AI usage. It also reviews employee AI literacy or skills, both soft and technical to determine gaps hindering full adoption.

For example, GitHub co-pilot is an AI-powered coding assistant that allows developers to write code faster. However, it is not utilized by all BUs. Determining if the delayed adoption or use of GitHub is due to learning program gaps, helps formulate concrete training and development action to enhance adoption.

The study also assesses employee behaviors as factors. These are identified as key contributors including adaptability, fear or anxiety (or enthusiasm) on the use of AI, and resistance to change due to lower confidence in AI use. It further evaluates the different employee engagement programs such as hackathon, process improvement initiatives, technology day event and reward system policies. These reviews are in relation to driving engagement to enable the employees to feel empowered to experiment and adopt AI use. It checks the existing incentives and recognitions for AI effort and how these contribute to higher employee engagement on AI adoption.

Data Collection Methods

Data sources such as survey forms, interviews and internal documentation were used to collect inputs and insights for this study. Data collection included focus surveys with open-ended questions completed by R&D employees from software and hardware teams enabling an understanding on organizational structure and AI literacy gaps, which includes competencies and skills' challenges encountered when using AI at work. Key informant interviews were conducted for the R&D employees and managers allowing a reflection on the issues they encountered related to adoption of AI in the workplace, including what works well that yields positive results. Project documentations and related reports were also reviewed as part of the analysis. Site level project reports and project meeting minutes that identify the number of AI pioneers, the number of Generative AI experts counted and number of AI projects categorized per BU summarized the productivity gains per design and development activity.

Sampling and Participants

The study used purposive sampling in selecting participants who were involved in AI projects and initiatives. The participants included R&D employees that were focused in software and hardware development. Sampling covered different business units within technology organizations in order to provide an overall view of the whole technology organization.

Data Analysis

This study employed a qualitative research approach combining contextual analysis and thematic analysis to examine factors influencing AI adoption within the R&D organization. Data sources are derived from interviews, survey responses and internal documentation from multiple R&D functions. These functions from different business units include software, hardware and testing. Experiences, perceptions, challenges and observed impact on AI use on productivity are captured. Contextual analysis was first applied to interpret responses within the specific R&D environment, considering processes, roles, governance, organizational structures and operational constraints. This analysis was followed by thematic analysis using an inductive coding approach to systematically identify patterns and themes across the collected data. These themes include organizational structure, employee engagement and behavior, AI literacy, governance and ethical considerations and its productivity impact. These were synthesized to provide an integrated understanding of the current AI adoption and to present recommendations for enhancing AI adoption across the R&D organization.

Scope and Limitations

The study examined the existing R&D employees of an industrial technology organization and its current AI adoption. The assessment included selected participants from R&D employees under the software and hardware design and development teams fulfilling both in an individual contributor role and R&D management responsibilities. It evaluated its organizational structure, organizational policies, employee engagement and behavior and AI skills and competencies.

Because the focus of the study is within a single organization, the findings were shaped by the chosen R&D organization characteristics and restricted generalization for other organizations. It was also highly specific to the productivity impact of AI on NPD Phase 4 because of the role selection of the participants. However, the study still provided practical relevance and actionable terms for the R&D workforce adopting AI that can be scaled to other organizational units and other R&D work beside design and development.

Data Privacy Statement

Participation was voluntary and consent from participants were obtained before performing the data collection. The participants' identities and responses were kept confidential and data was anonymized during analysis with no personally identifiable information to be disclosed. The study complied with the ethical approval process.

VII. RESULTS AND DISCUSSION

In order to provide a thorough analysis, insights were derived from survey responses, semi-structured interviews and internal document reviews based on four main thematic enablers defined in the research framework. These themes included (1) organizational structure, (2) employee behavior and employee engagement, (3) AI literacy, (4) organizational policies and ethical consideration in the AI adoption to drive productivity gains. The overall observed productivity gains because of AI with R&D work were tackled, which demonstrated clear benefits that were observed in its current state. With the research framework as the basis, a structured process was applied determining patterns that emerged from the data analyzed. By conducting triangulation on various data sources, the findings validity was strengthened. This ensured the alignment between the results of the study and their practical application in the aim to enhance organizational productivity. The following summarized the results for each theme:

1. Organizational Structure

Feedbacks from both survey respondents and interview participants highlighted the organizational challenges due to the absence of formal structures or well-defined roles for AI adoption. Across different BUs, the organizational structure was evaluated. This covered gathering information on how AI direction and strategies were managed. Survey responses for the organization structure were within effective and somewhat effective, with ranges of 60% to 70% of respondents favoring the current state. This provided opportunity as a third of respondents saw improvement on this area.

The majority of survey respondents noted that AI work is simply handled as added task within their existing roles; thus, were informally done. This observation was reinforced by interview results with employees describing the organizational structure as like silos where some functions were performed through an ad-hoc approach. As some respondents indicated during the interviews, “everyone can make their own AI agent, but at the project level, there is no clear direction or standards”. This posed some critical issues on alignment, indicating the gap between the team-level approach and the organizational goals and strategies. As a consequence of informal assignments on AI responsibilities, clarity on AI project ownerships was lacking and often not prioritized compared to other operational deliverables. An interview with one software test engineer noted that he explored AI learning during weekends because his capacity was full during regular working days. Another team member also noted during the interview that when there are competing priorities, AI efforts were treated as “just side tasks parked once projects come in”. The absence of clear organizational structure and support through time allotment, roles assignment and cross functional team collaboration negatively impacted a consistent and accelerated adoption at R&D work. Review of internal documents supported this finding with the published organizational chart that showed no clear delineation about AI roles and responsibilities.

The data derived from surveys and interviews also suggested top management members have not fully integrated AI on its overall organizational makeup. Multiple survey respondents have asked to strengthen top management’s take on providing AI direction and alignment citing the need to improve on this area so employees can understand and relate the roles they play within the high-level organizational AI strategies. Multiple functional managers were already driving AI use but not in a standardized manner. Only PWS included goals or key performance indicators (KPIs) with AI objectives. The absence of formal support to integrate AI in R&D work by having dedicated AI engineers, capacity for AI work and uniform strategies across all functional groups and business units, impeded the ability of the organization to accelerate adoption. If AI will continue to be treated as a side work instead of a conscious and deliberate push, the organization will be missing out on potential contributions of the high technology that can drive and enhance performance and productivity.

PSS was heavily implementing a bottom-up AI strategy as it is driven largely by local needs and individual initiatives instead of a clearly articulated top level AI roadmap. Collaboration existed in a reactive and situational manner since teams collaborated when an issue happens. RS combined strong bottom-up execution while recognizing a need to have a more top-level structure since reliable project-level outcomes are seen. However, there was a need to provide a structured governance and standardization of tasks or roles for a more consistent implementation across the department. The presence of formal governance in PWS indicated it is predominantly using a top-down approach in deploying its AI strategy. The presence of dedicated PWS AI engineers, formal governance structure, explicit discussions on AI roles, committees and approval processes indicated how AI initiatives were framed as organizational capabilities instead of optional experiment or side projects.

Key patterns also showed that PSS achieved organizational benefits in software development, hardware development and testing while some collaboration existed and result varied that was dependent on the person championing the AI initiative. RS achieved outcome with some uneven level of consistency varying project per project. PWS had more predictable and repeatable gains through a governance adoption. A matrix summarizing the BU specific approach, collaboration level, structure and variability on achieving goals was presented in Table 7.1.

Table 7.1.

Business unit structure vs AI goals achievement

Business Unit	Localized Approach	Structure	Goals Achievement
PSS	Champion-led. Some cross functional collaboration exists between sub groups such as software teams and test team	Ad hoc	Localized or individual productivity gains achieved in NPD Phase 4
RS	Project-specific leadership and coordination seeking	Ad hoc	Project level productivity gains achieved in NPD Phase 4
PWS	Local board proposal. Collaboration was structurally enabled	Formal governance	Scaled productivity gains achieved in Phase 4 and other phases such as Phase 1

2. Employee Behavior and Engagement

The employee engagement on AI adoption was noted to be uneven. Survey respondents shared there are early adopters who are very eager to use and apply AI in their R&D work but also shared how they observed some members of their team demonstrate reluctance to adopt early. According to multiple employees interviewed, they observed that the general level of employee engagement on AI use ranged from moderate to high. These discrepancies existed with one manager interviewed noting “a high level of engagement with AI among colleagues” while a software engineer responded on survey “a reluctance to accept that AI is needed to be integrated into our tools and workflows”. However, what was seen as an overall trend in data gathered both from surveys and interviews was that project deliverables were taking precedence over AI learning and AI work. There was an absence of dedicated time or incentives. Effort relied on the engagement on employee’s personal drive which created variability on AI effort and results among R&D employees. There were those who were highly motivated to experiment even using their own time to use AI and were able to experience its value firsthand. As shared by one software engineer survey respondent “it helped me work smarter, not harder”. Meanwhile, there were those who don’t allocate much effort as it was not seen as a pressing issue. The mixed engagement level captured the human factor and the need for cultural change so AI can be institutionalized as part of day-to-day R&D work to ensure consistency and sustainability of its use across different functional groups.

Distinct employee engagement and behavior patterns per business units were also observed. One aspect reviewed was the incentive and rewards system in relation to AI adoption which was determined to have a variability on survey responses across BU. PWS showed all neutral results and interviews also highlighted that formal incentives were not the one driving employees to use AI. Instead, it was driven by personal productivity and gains realized by the employees. RS was mostly neutral with respondents who felt rewards existed but was not fully working. PSS was mixed with some highlighting the need to leverage existing reward systems for AI related contribution, with recognition seen as the simplest incentive, which when tied to performance metrics can sustain engagement.

PSS was also seen to exhibit task-driven AI behavior. They used AI to automate repetitive task data creation, reporting, analysis and software code optimization. They demonstrated cautious behavior, highlighting the need to validate results, comply with ethical use and handle sensitive data properly. The culture of experimentation for this BU was mixed, with some proactive individuals experimenting actively on AI tools; while others initially showing interests but when faced with certain barriers, would immediately abandon the effort or initiative. They collaborated locally within their own teams, limiting opportunities for wide collaboration as there were no formal mechanisms defined. RS employee behaviors were anchored on projects. Their engagement varied per team. Some showed proactiveness in experimenting but were hindered by time limitations and approvals. Their AI usage was concentrated within their project teams and they collaborated and provided peer support as needed on their projects. PWS employees displayed a more embedded and structured AI behavior as it was normalized in their daily work for analysis, decision making and workflow streamlining. They demonstrated interest in AI experimentation specially in software teams. They participated in structured initiatives and identified that leadership alignment allowed for sustained AI use.

A summary of employee engagement and employee behavior per business unit based on survey and interviews is presented in Table 7.2.

Table 7.2.

Business unit employee engagement and employee behavior vs AI goals achievement

Business Unit	Employee Engagement Level	Employee Behavior	Variability on AI Goals Achievement
PSS	Moderate	Task-driven, self-directed learning, cautious, individual	High variability due to dependency on individualized productivity gains
RS	Variable	Project anchored, peer supported	Moderate and varies project per project
PWS	High	Structured participation, embedded AI use	Low variability due to structured participation and embedded AI enabled behavior

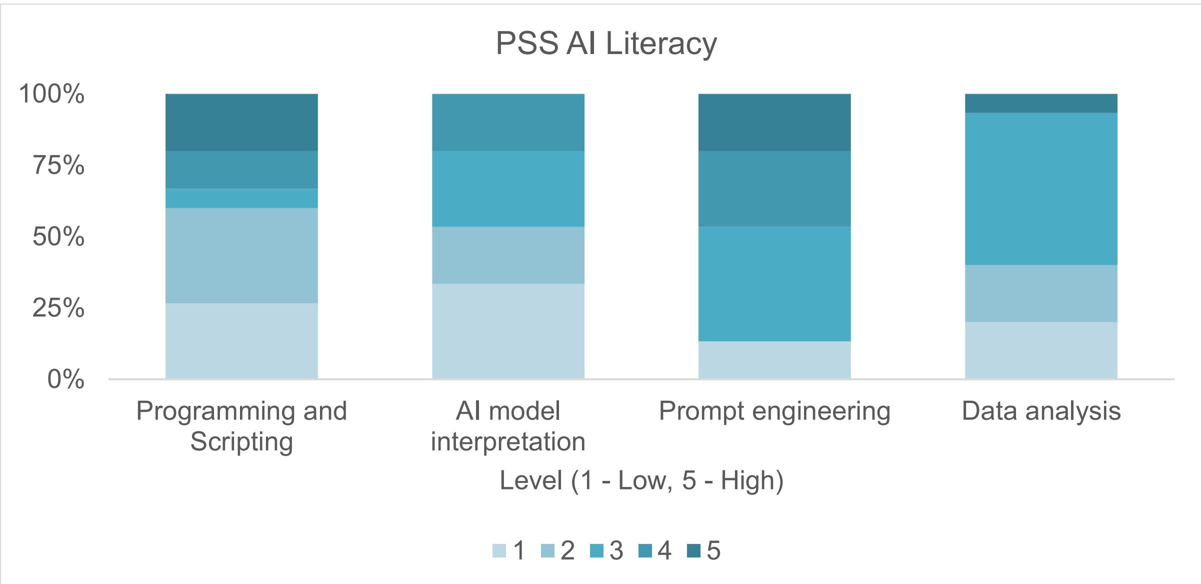
3. AI Literacy

Both surveys and interviews found AI literacy level as a limitation among many R&D employees in achieving effective use of AI for productivity gains. Even employees in software development teams who already have strong software background and can easily translate similar competencies on learning AI, still lack in-depth AI knowledge for increased effectiveness and for maximizing the features available in AI tools. For R&D employees without software development expertise, it became a more defined barrier. One interview noted a software tester found the use of AI difficult to apply in her work because of the absence of programming familiarity adding “most of the AI learning requires programming, but my task is software testing and it’s hard to understand”. Programming/scripting proficiency was found to be a common theme that needed improvement on all functional groups since the available AI tools required coding and a level of understanding of what should be its corresponding output. One survey respondent shared, “Programming skills should also be strengthened to better understand the training sessions being offered” which correlates coding ability with AI utilization. Beyond programming, “prompt engineering” was also found to be a skill that required improvement since R&D employees found that their interaction with AI assistants provided fewer ideal results. AI hallucinated or provided invalid, false, or inaccurate responses, if the way they sent queries were not properly prompted.

The data also indicated, given that there were existing AI skills gaps, many of the employees were still learning about AI through self-instructed training since formal training was not common. From the survey data, more than half of employees surveyed were learning AI on their own, by taking online videos and tutorials and trial and error, instead of a formal learning format. This resulted in varied levels of skills development across the organization. Some became knowledgeable faster than others while others gained limited progress. Most of the survey respondents indicated that the generic AI awareness sessions were not enough to translate learning into actual results. One hardware engineer cited that he welcomed the basic AI sessions provided but noted these were “not enough; engineers need hands-on relevant examples” if it will be applied on their functional activities. The absence of hands-on or domain specific training sessions caused difficulty in effective and practical implementation of AI in their roles. More importantly, a common theme was the absence of allocated hours to upskill in learning AI since the same set of engineers, who were expected to use and develop AI tools at work, were also responsible for producing project deliverables. One survey respondent added “since they handle multiple projects, they often don't have enough time to dedicate to learning AI". These gaps on employee AI skills, the absence of formal and role-based training and lack of dedicated time for AI learning were factors that were affecting more AI adoption as it impacted employee's confidence and ability to leverage the full potential of AI at their R&D work.

Figures 4, 5 and 6, showed the distribution per level in a particular area of AI literacy including programming and scripting, AI model interpretation, prompt engineering and data analysis, based on 5-point rating scale, with 1 at low point and 5 at high point. Prompt engineering was the strongest skills across BU with more than 50% of respondents rating themselves between 4 to 5 skill level. AI model interpretation the most consistent gap particularly on PSS. Based on the survey, PSS also had the largest beginner population, at 60% with low rating; indicating a need for structured upskilling. Figure 7.1 showed the PSS AI Literacy Survey Result across the 4 AI key domains.

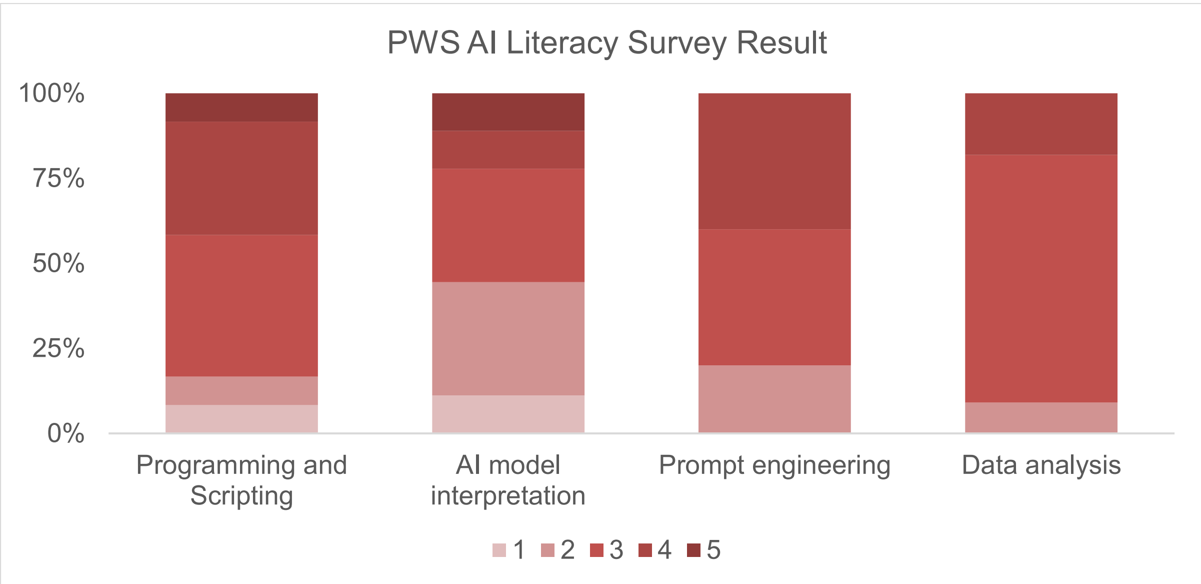
Figure 7.1. PSS AI literacy per category survey result.



This translated to the ability of the PSS team to interact with AI tools effectively but had challenges in evaluating the AI output critically and producing repeatable or automated AI-enabled solutions. This resulted in PSS achieving uneven productivity gains across the department and were limited to individuals as opposed to teams. PSS was at a moderate but imbalanced maturity stage that required targeted upskilling on interpreting the result of AI to unlock more consistent gains.

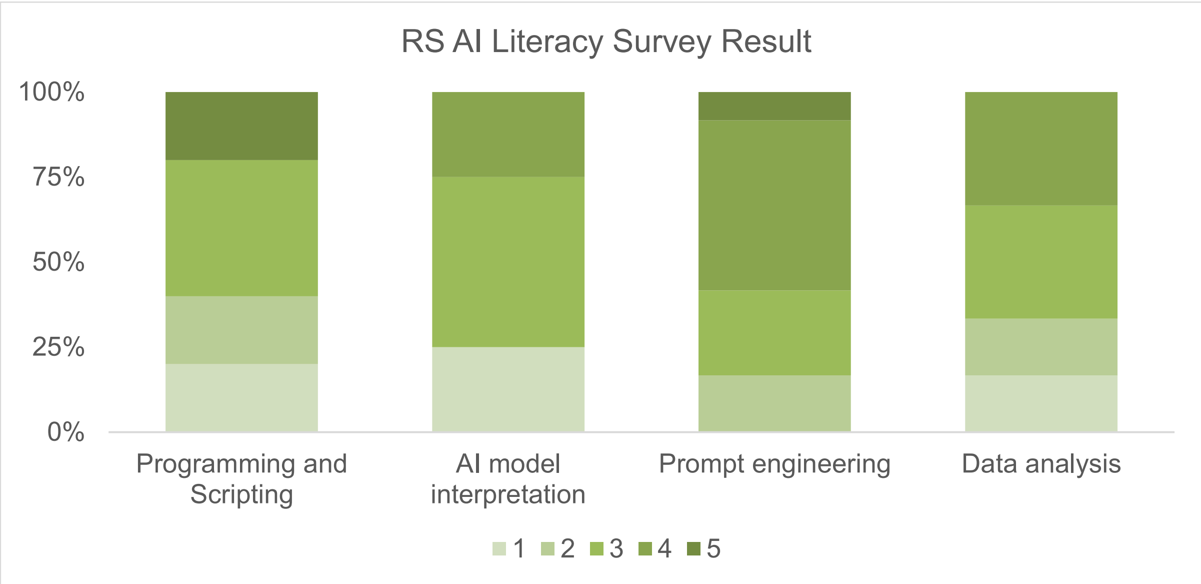
PWS was generally strong in data analysis and prompting but needed a boost in programming and AI model interpretation. Their literacy assessment was balanced as many were at midrange that enabled them to convert AI usage into practical productivity improvements covering research, analysis and development. Figure 7.2 showed PWS AI Literacy Survey Result across the 4 AI key domains. These gains remained to be incremental and there was a need to deepen the technical literacy for advanced use case to achieve maturity on AI literacy.

Figure 7.2. PWS AI literacy per category survey result.



RS showed programming, scripting and prompt engineering as high strength but needed to provide extra focus on model/output interpretation and verification. RS was positioned well to embed AI into their workflow instead of keeping within the assistive feature of the AI tool as they also rated high on data analysis which was an advantage in capturing measurable gains on project level. Figure 7.3 showed the RS AI Literacy Survey Result across the 4 AI key domains.

Figure 7.3. RS AI literacy per category survey result.



A summary of AI literacy per business unit and its results on achieving goals was presented in Table 7.3.

Table 7.3.

Business unit AI literacy vs AI goals achievement

Business Unit	AI literacy Observed Maturity	Goals Achievement
PSS	Moderate maturity with skills imbalance	Productivity gains vary depending on employee skills and motivation
RS	Strongest maturity in programming/scripting and prompt engineering but interpretation is still a gap	Productivity seen on measured hours saved for coding and testing on project level
PWS	Higher maturity given there are existing embedded AI engineers within the organization with strong data analysis	Real productivity gains recognized on different NPD activities including research, coding, and testing

4. Organizational policies and ethical consideration

The surveys and interviews revealed various observed issues related to organization policies, governance, and ethical considerations in the use of AI in the workplace; some were common across all Bus, while others were BU specific context. The three (3) more common issues were lengthy approval process for AI tools and infrastructure, ambiguity in AI policies for use of AI tools and applicable permission and absence of formal ethical awareness program.

(1) Timing of Approval Process for AI Tools and Infrastructure

Participants of the survey and interviews reported proper timing as a challenge when requesting AI related subscription and cloud-based virtual machines needed for AI experimentation. They highlighted that even with the existence of managerial support, the presence of multiple layers of approval causes delays in issuance of licenses and subscriptions; thus, it remained problematic given the fast-paced nature of AI technology.

Meanwhile, PWS main challenge was associated with difficulty in accessing infrastructure for AI experimentation, including those at early stage of exploration. This was under the concern on timing of approval process for AI tools and infrastructure. However, despite this, immediate productivity gains still became pronounced and realized after challenges on approval were overcome. The respondents also recognized that ethical requirements were needed but can be fulfilled outside of the workflow instead of being integrated into the day-to-day activity. This impacted the time-to-value, or the ability to apply AI immediately because proof of concept or proof of value was also delayed.

(2) Clarity on AI Usage and Permitted Tools

Respondents from all BUs identified existence of high-level AI policies. However, they reported insufficient practical guidance on permissible AI tools and usage at the functional level. As such there was confusion on what and to what extent AI tools can be used. For example, the respondents shared boundaries associated with the use of public AI Application Programming Interface or API for translation tasks or generative AI tools used for coding or development. These restrictions were discovered after usage of the tool, reinforcing a more cautious approach prior full adoption in each department.

(3) Absence of Formal, Practical, and Ethical AI Related Trainings

The data collected revealed that all employees, regardless of BU was at a fundamental level of responsible use of AI awareness; that was, the AI usage raised critical ethical, security, and intellectual property considerations, particularly when handling proprietary or sensitive information. However, employees noted they achieved this know-how mainly using self-instructed training because formal guidance thru structured training was limited. This was observed to be a common raised concern across all BUs.

On the other hand, with respect to BU specific context, PSS provided higher emphasis on IP protection, data security and AI accuracy, restrictions imposed on external AI tools, and the absence of role-specific workflow. All of these were under the general concern on AI usage and permission. In the absence of clarity on how the AI output can be validated, engineers incurred additional expenses to analyze the AI results. This delayed expansion and scaling up as this process require waiting time for approval for process alignment.

Finally, RS BU reported that the absence of formal structured training created gap in understanding the reliability and accuracy of the AI outputs received. The learning approaches done remained at the project level and without a standardized learning, the results achieved were only incremental and varied instead of transformational.

A summary of organizational policies and ethical considerations for each business unit and their results in achieving goals was presented in Table 7.4.

Table 7.4.

Business unit main organizational policies and ethical consideration issues vs AI goals achievement

Business Unit	Organizational Policies Issues	Ethical Consideration Issues	Goals Achievement Impact
PSS	Restriction on use of external/public AI tools	Strong concern emphasized on IP protection	Due to employees understanding on the risks in using AI, adoption of tools was selective and constrained. It lowered opportunities for more productivity gains.
RS	Gaps on standardization in integrating AI at work	Ethical AI guidance was self-learned instead of receiving through a role-specific cascade. Employee emphasized concern on the correctness and reliability of AI output	Adoption was pragmatic as it applies to project level or use case driven. Gains remained tactical due to limitation in approach for wider level of integration.
PWS	Long approval process even for early experimentation	Ethics were conceptually understood but applied in the operation outside of the day-to-day and standard workflow. Workforce impact and change management concerns also surfaced more explicitly	Once approval was received, the productivity gains accelerated. Scaling for broader adoption was limited by the policy on approval instead of employees' concern on ethical use.

Productivity Gains in R&D from AI Adoption

A significant finding of the study was that despite the identified challenges, AI applications in the R&D work of the case organization were getting actual results, and identified benefits. There were multiple examples from survey respondents and interviewees that highlighted how AI in R&D work helped them in increasing productivity, translating enhanced capacities into work improvements, thereby efficiency and enhancing quality outputs that decreased the need for rework. These were summarized into three (3) measures of productivity gains, such as (1) FTE & cost savings, (2) faster development time (3) manual effort reduction, which were mapped to NPD activities including design and development, review and testing, documentation.

FTE and Cost Savings in R&D thru AI Adoption

FTE and cost savings were mainly realized as capacity gains rather than headcount reductions when developers and testers saved time to deliver more work. Table 7.5 summarized these savings per R&D activity.

Table 7.5.

R&D activity and FTE & cost savings achieved thru AI

R&D Activity	FTE & Cost Savings
Design & Development	Large effort reduction was translated to increased capacity rather than headcount reduction. Examples included 60% productivity gain in software development tasks and 85% effort reduction when week-long coding and research tasks were reduced to one day

Review & Testing	Survey responses indicated that employees were achieving 60% more testing output due to time savings enabled by AI. Cost savings were implied through increased capacity to design and develop more new products but not monetized in the survey or interview
Documentation	Savings were described qualitatively through reduced time spent on documentation and reporting

Faster Development Time in R&D thru AI Adoption

Cycle time improvements were seen as not isolated to one type of activity as it also covered coding, analysis, testing and troubleshooting and documentation which were associated with automating repetitive tasks and faster access to information reinforcing faster development velocity. Table 6.6 summarized these faster development time per R&D activity.

Table 7.6.

R&D activity and faster development time achieved thru AI

R&D Activity	Faster Development Time
Design & Development	Multiple respondents stated development tasks were completed in half the time with AI use including analysis tasks that reduced a 4-hour work into an hour representing a 4x cycle time improvement. Software developers also reported significantly faster coding, debugging and research time when using AI assistant. These include code generation and code fixing tasks.
Review & Testing	Both survey and interviews reported faster test cycles with the use of AI to handle build generation of test cases and test data. With the use of AI in setting up, test review and execution, more scenarios and broader coverage were captured within the same time frame.

Documentation	With AI support, documentation, reporting and translation were described to be faster compared to executing the task without AI. Compared to fully manual documentation activities, there were quicker generation of write-ups, summaries and reports when AI is used

Manual Effort Reduction in R&D thru AI Adoption

Manual effort reduction was a main enabler across R&D activities which was achieved through automating repetitive activities. Table 6.7 summarized this manual effort reduction per R&D activity.

Table 7.7.

R&D activity and manual effort reduction achieved thru AI

R&D Activity	Manual Effort Reduction
Design & Development	AI was used in code generation, debugging, research and data analysis which were typically done manually or without any AI augmentation. There were also routine development tasks highlighted by respondents such as initial draft and exploratory analysis that can be done by AI allowing employees to focus on higher value activities on design and problem-solving work
Review & Testing	Manual test data preparation, repetitive test case creation and maintenance were being automated allowing for manual effort reduction allowing for employees to redirect their effort on test analysis and test strategy
Documentation	Routine documentation and reporting were repetitive work that were being AI assisted. AI also helped in generating initial drafts and structure output improving documentation consistency

VIII. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

The following summarizes the main observations from this study; conclusions derived from the achievement of the research objectives as well as presenting recommendations to enhance AI adoption in an industrial technology organization. These are captured based on the contextual and thematic analysis derived in data collected from survey forms, interviews and review of internal documentation. The findings and observations are organized based on the four enabler themes identified in the research framework.

The study found a significant potential for the adoption of AI in achieving productivity gains in an R&D workplace, specifically for software and hardware design, development and testing in an industrial technology organization. However, the study also revealed several challenges to achieve higher adoption at the organizational level. These challenges, among others, include issues on formal strategy for AI integration in the workplace, AI skills and literacy gaps, bureaucracy of approvals, weaknesses on guidelines and governance concerns. Upon review and analysis of survey form responses, interviews, and internal documents, it uncovered key areas aligned with themes defined in the research framework.

Absence of Formal Organizational Structure Constraints the AI adoption

It is not the lack of interest among employees that is impacting a consistent and sustainable adoption. Given that AI efforts are being executed informally, instead of having a structured organizational framework with defined roles, responsibilities and ownership, the AI adoption in R&D work is not consistently applied and the desired speed is unmet. The current AI deployment is largely bottom-up approach wherein AI initiatives are initiated and driven by individual contributors, informal groups or AI champions. The experimentations are done in silos and as one employee respondent reported, "anyone can create their own agent, but there is no project level direction or standard to guide them". The absence of a unified strategy with defined objectives and targets cascaded top-down, is leading to varying adoption level. A stronger leadership drive and intent, with clear AI vision and roadmap will support seamless integration of AI across all R&D activities. As revealed in the study, this differs from the current state wherein AI initiative is seen as an ad-hoc work instead of being treated as a strategic operational directive.

Employee Behavior and Engagement is Shaped by Structure, Leadership, Skills and Policy Clarity

There is a split between early adopters who take initiative and actions on using AI in their R&D work; and those who are laggards, or those with reported reluctance in adopting AI in their activities due to some valid reasons. The proactive engineers are "personally motivated and curious" because of their positive experience with AI use noting "experienced firsthand benefits such as increased efficiency, better insights, and time savings". While those who are late to adopt are seen to resist due to being cautious, with low interest to learn, use or apply AI in their R&D work, as they are too engaged in their day-to-day functional commitments. A comparative effect of employee behavior and employee engagement between software teams and hardware teams are summarized in Table 8.1:

Table 8.1.

Comparative assessment of employee engagement and behavior and the effect on AI use between software and hardware teams for PSS

Aspect	Software Teams	Hardware Teams
General engagement level	High – based on survey and interviews, software teams are intrinsically motivated to use AI due to the seen software development benefits thru AI automation and high familiarity in coding	Low – based on survey and interviews, hardware teams perceived AI tools as less directly applicable to their core activities which deals with physical hardware
Nature of engagement	Voluntary, exploratory	Cautious, problem-driven
Frequency of AI Use	More Frequent	Sporadic
Engagement Drivers	Speed, automation, peer examples	Specific need, perceived safety
Engagement Barriers	Time pressure	Time pressure, risk concerns
Effect on AI adoption	Faster, broader use	Slower, limited use

Based on the study, employee engagement did not emerge independently. It is modeled and exhibited based on existing structure, leadership, individual skills and clear policy cascaded. Given there is wide variation in engagement, as some employees actively experiment with AI while others perceive it as extra work or competing within their other priorities, employee engagement is highly important as it determines whether AI enablers will translate to actual usage.

AI Literacy is a Foundational Prerequisite

Skill gaps in applying AI in R&D work were also observed attributed to absence of technical skills and AI know-how necessary to successfully implement AI that will result in tangible benefit. Knowledge in programming is viewed as a competency that helps software engineers to apply AI in their work activities. As such, lack of it is identified a disadvantage to those who are not software developers. Prompt engineering is also noted as one AI literacy that is found useful for effective use of AI assistant-based tools; even though 1 in 2 survey respondents rated themselves low to moderate on this skill. With these gaps, engineers are learning about AI concepts mostly on their own with limited formal training offered which they expect will include hands-on work tailored to their roles. With skills gaps and the lack of dedicated time for AI learning, even with engagement and structural support, the effective use to maximize AI adoption for more productivity gains is compromised.

Unclear and Overly Restrictive Governance Hinders Confidence on AI Use

The approval processes around AI tools are cited as a pain point by engineers because of the time it took to get the resources, such as software, hardware and cloud resources, they need. The lengthy and tedious workflow has affected the ability of engineers to stay agile on AI adoption, creating hesitation and discouragement for others to further experiment on new AI tools. On the aspect of ethical and security consideration, only two respondents indicated they have limited knowledge on this topic as the majority shared that they are aware of the need to properly protect data including when dealing with AI. However, despite this, many noted there is only minimal formal training on AI ethical use and is noted as a gap when it comes to organization led awareness campaigns. This shows that the absence of policies and clearer understanding on what are off limits versus what can be done, is impacting the practical application of AI and affecting the higher R&D employee adoption of AI. For hardware engineering for example, IP sensitivity is high and fear of violating policies is discouraging experimentation.

These challenges in current AI adoption in R&D are organizational and spanning structure, engagement, skills and governance instead of solely being influenced by technical limitations.

Clear Productivity Gains in R&D

As observed, when AI is meaningfully adopted in R&D workflows, multiple benefits are achieved including faster task completion, automation of repetitive tasks, quality improvement through consistent and standardized output, time saved in analysis, testing, verification and documentation and ability to focus on high value work. These are seen in different types of roles and all BUs involved. Software development observed productivity gains on AI use in automating code and debugging. Hardware development realized productivity gains through data analysis and design verification. Test engineering recognized benefits through the use of AI in test case generation and reporting. However, the productivity gains are uneven with some benefiting on individual level, others on project level but not scaled out across the organization.

AI Readiness in Software and Hardware

During survey and interview sampling, the respondents include members from PSS software and PSS hardware teams. No other representations were made for other hardware teams; thus, BU comparison analysis is limited to PSS. Both PSS software and hardware teams lack formal organizational structure although software teams appear to be more adaptable based on AI experimentation within their existing workflow. Hardware teams experience more structural constraints due to the absence of clear ownership and complexity in integrating AI in hardware processes. Across both groups, the absence of formal AI structure limits sustainability and scalability of use of AI at work. Table 8.2 summarizes the comparative assessment between teams.

Table 8.2.

Comparative assessment on AI Readiness between software and hardware teams for PSS

Aspect	Software Teams	Hardware Teams
Dedicated AI Roles	None	None
Formal AI Structure	Absent	Absent
Nature of AI work	Informal, Experimental	Informal, Activity-Driven
AI Ownership	Individual enthusiasts	None, fragmented
Perceived maturity	Early stage but progressing	Early stage and constrained

Conclusion

The study initially provided a framework that includes organizational and workforce factors identified as enablers to drive higher AI adoption toward achieving productivity gains. Based on the result of the study, it concluded that organizational factors affect employee behavior and engagement on an enhanced AI adoption towards R&D productivity gains. The primary drivers are found to be organizational structure, AI literacy and skills, policies, governance and ethics while employee behavior and engagement did not emerge as an independent factor but a response to the underlying organizational environment set, with it mediating how the organizational capabilities of AI will translate to actual use. The utilization of AI at work as part of AI adoption leads to real productivity gains as its resulting outcome.

In the study, it was observed how the organizational structure enabled the AI adoption, which assessed that R&D teams are operating without dedicated AI roles or formal ownerships. Instead, AI R&D work is included as additional activity on top of the existing responsibilities and the management of these initiatives are normally handled informally within various groups. The absence of formal structure resulted in fragmented effort, accountability confusion and de-prioritization when the main job competes with these AI efforts. When this occurs, the employee's decision whether to use AI or not varies widely. For organizations with strong push from their management team, AI receives importance and resources are provided. For those without, the employee engagement may or may not support the continuity of AI effort to sustain more productivity gains.

The second driver that influences employee engagement to use AI at work is the presence (or absence) of needed skill to continue with the AI effort. The study found that majority of the employees rely on self-instructed learning and build their AI competence through informal resources. The development of employees on AI competency becomes uneven depending on the effectiveness of the self-learning approach and their own internal confidence in applying AI on their R&D tasks. Those who do have any practical skills yet to use AI tend to limit experimentation. When skill gaps persist, engagement on AI use remains inconsistent.

The policies, governance and ethical considerations influence employee engagement and behavior. The study noted that there were multiple concerns on unclear guidelines, delay on approval process, concerns on data and IP security and ethical use leading to hesitation and risk-averse mindset. Employees shared that they want to use AI tools but are unaware of existing boundaries on what is permitted and steps on how to ensure these can be used responsibly at work. Achieving high engagement of adopting AI becomes dependent on individual assessment on organizational risks associated with AI use because of unclear and restrictive governance on what is allowed for experimentation. By having clear guidelines on the responsible use of AI and by streamlining the approval for AI tool use, employee engagement will elevate for more AI tool adoption.

The study noted that engagement reflects how employees understand and respond to the existing organizational structure, skills readiness and governance and direction. It indicated that AI efforts that were formally recognized enable the employees to allocate time for experimentation. In addition, formal trainings complemented employee engagement to use AI tools when there is more certainty on what is allowed and what is not permitted.

As AI adoption is achieved, the study identified that enhanced productivity gains will be the resulting outcome. These improvements include efficiency, quality and time utilization including faster task completion, reduction of manual work and enabling more capacity for high value R&D activities.

The study emphasized that employee behavior and engagement towards AI adoption are impacted by organizational factors. To enhance AI adoption in R&D, it will require coordinated effort and improvements in organizational structure, AI literacy and governance. These drivers when addressed will develop a condition wherein the desired employee engagement and behavior needed will result in scaling up AI adoption in R&D that is sustainable.

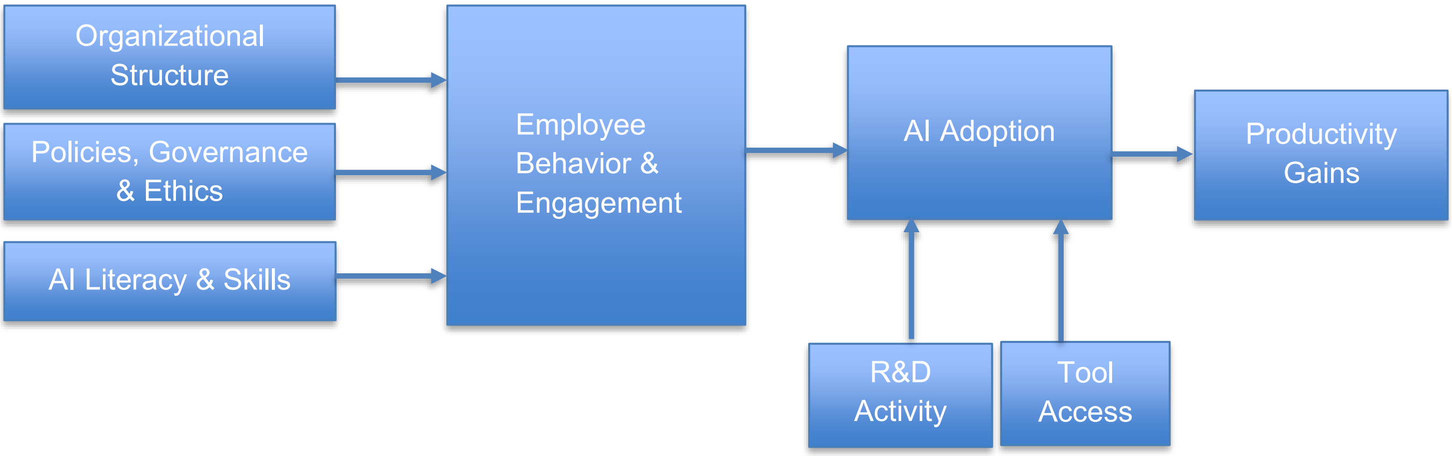
Recommendations

Tien et al. (2025) stated that the use of AI is best to be leveraged for process optimization and predictive analysis enhancement to drive growth in an R&D organization. There are several strategic and operational recommendations that the industrial technology organization can do to enhance AI adoption in R&D work consequently enabling higher productivity gains. These includes addressing organizational structure and policies, strengthening governance and ethics, improving AI literacy and skills and improving the employee engagement and behavior. These recommendations emphasize strategic initiatives on the use of AI to enhance and expand R&D employees’ skills and capabilities, not to replace human expertise.

Framework on AI adoption and R&D Productivity Gains

A proposed framework to guide the organizational transition towards enhanced AI adoption in the workplace as shown in Figure 8.1 is recommended to be applied in the R&D organization.

Figure 8.1. A framework for enhancing AI adoption toward R&D productivity gains.



This framework emphasized that organizational structure, policies, governance and ethics and AI literacy and skills are foundational conditions. These factors shape the organizational readiness and capability of its employees to use AI. These influence employee behavior and engagement which dictate employee's motivation, confidence and willingness to use AI at work. AI adoption acts as a central mechanism to translate these actions into impact while R&D activity and tools access supports the actual R&D tasks. Once AI is effectively adopted in R&D activities, productivity gains are observed.

Organizational Structure Improvements

Rudko et al. (2021) noted that organizational fit with AI strategy is recognized to be of key importance to maintain competitive advantage. For this study, as part of organizational alignment, it is recommended to transition from having ad-hoc integration of AI in R&D work, to an organization supported by clear structure and roles for AI related R&D tasks and activities, while setting up defined goals and objectives associated with AI. The current effort on AI falls under “part-time” and when operational commitment competes, the AI work is deprioritized. By having a defined AI team or committee, driving and coordinating projects across different groups, it will offer a more deliberate and structured ownership and accountability. Formally integrating AI learning, experimentation and work within the NPD 4.1 phases, will also ensure AI focused effort. For teams that use agile methodology within NPD, innovation sprint offers work hours for I&A (Inspect and Adapt) tasks to be reused for AI related effort. In the same way, by having specific goals, AI progress will be measured with firm targets driven from top-down. The organization will need to limit relying heavily on the interest of employees to adopt AI through their own effort. Instead, it will need to transform the AI initiatives to AI projects with allocated budget and resources. This will be a more sustainable approach. It is recommended to create strategies to transform R&D employees into more active AI users. Formal incentives on AI use are recommended to enable a culture of experimentations. Enhanced top management engagement will initiate a mindset shift to employees relative to AI being perceived as an add-on or optional work. When leaders are showing they are also engaged with AI use, R&D employees will look at AI as a requirement within their own activities. R&D managers will need to provide constant and consistent messaging about AI use as a requirement. These can be realized by providing reward and recognition for success stories on AI use. The organization also need to establish a formal avenue for “safe to fail” AI environment to remove the pressure on employees on doing things right the first time. Finally, the managers have to share examples of their own AI successes to further influence their direct reports. These approaches will sustain the interest and continuity of AI effort including those that are on the fence or are too busy to use AI. As mentioned by one survey respondent, the “no one is left behind” strategy will enable broader engagement within the whole R&D organization.

AI Proficiency Improvements

Kesby (2025) noted that role redesign in the organization will be necessary as the traditional organization will evolve to include AI agents as part of the team who will support the existing employees. He added that employees will be expected to use AI on the daily basis requiring a need to conduct skills and knowledge audit to understand gaps for each employee. It is therefore recommended to invest in AI proficiency improvements that are targeted and tailored to each individual role. Low AI literacy is seen as one of the key barriers in enhancing the impact of AI in employees’ productivity since those who are less knowledgeable and less skilled on AI’s full potential are experiencing challenges to translate them in the actual application. More importantly, confidence is gained when they feel competent to use it well. For those with reluctance in adopting AI in their R&D activities due preference for role preservation, communication strategies are required. Clear messaging on the AI intent and direction, as skills and capability augmentation to gain higher value engineering work, will need to be communicated and emphasized. As per data gathered in many respondents, the interest of employees on AI use is already a given. Many have a personal drive to explore and recognize the benefit of AI at their R&D work to help them do their activities faster and easier. The training investment will have to come through a more formalized structure program, that includes hands-on workshops and consultations with experts, which will augment engineers' self-learning. By offering advanced upskilling for interested employees and implementing role-specific AI training programs, the organization can strengthen R&D capabilities while ensuring AI adoption enhances.

Develop an Adaptive AI Governance

Lin (2025) highlighted the importance of balancing risk management with the pace required for innovation. It is therefore recommended to evolve AI governance that is adaptive with cross functional collaboration that ensure all technical, ethical and operation issues are covered. Multiple constraints are experienced by employees on the existing policies. These have to be reviewed to see an opportunity wherein risks are managed while employees are given more flexibility to test things out, such as setting up an internal AI sandbox, early engagement for new tools and solutions available and an option to bring down decisions to a local AI review board appointed by the site. A tier approach AI governance with members that are on ground can provide a more practical approach without compromising compliance to corporate level rules and policies. Such governance will also assist in creating accountability for training employees on ethical and responsible use of AI, expediting approval for software and hardware needs and improving channels and communications for questions and reporting.

Future Research Directions

The findings of this study can be extended and applied to other research directions. One of these is to look into the application of higher AI adoption beyond the Phase 4 or design and development. There are deliverables that are defined during market study and concept review. Additional case study that can be conducted is to determine if a common framework will also apply if similar productivity gains will be captured within earlier new product development phases. A good candidate is for initial phases of idea generation and concept feasibility wherein the main deliverables are associated with arriving on project charter and business plans. Because AI tools are known to optimize effort in documentation creation, the potential for this part of R&D activities will be applicable.

Another research opportunity that can be looked into is the application of the same framework within the dynamics of the global organization. The study is associated with the working environment within the local organization based in the Philippines. The productivity gains for hybrid teams wherein projects are being done by engineers coming from different parts of the world in a global technology organization is not within the scope of the study.

Finally, further research can be extended in the AI adoption for an R&D organization under industry focused on commercial applications, products and solutions. The similarity in the requirement in NPD for different types of industries will enable options to explore transferrable practices and check the applicability of this defined framework.

IX. PERSONAL LESSONS LEARNED

This research provided me an opportunity to be front and center on the organizational direction and move in having more AI-enabled R&D operations. There were four main area of focus including organizational structure, employee behavior and engagement, AI literacy, organizational policies and ethical consideration. Significant progress was observed on these areas while the study is being performed. The regular updates which were presented to stakeholders on each phase of the research from planning, preparation, conducting surveys and interviews were helpful to drive this progress. Partial results and initial thematic analysis were shared to the management team. This made the study more meaningful to ensure alignment on what requirements were needed. It allowed for an effective feedback mechanism and enable any necessary adjustments which can be applied immediately. In the AI adoption and organizational structure for example, since the study began, incremental improvement was seen on the AI integration to the operation. A holistic adoption of AI for Software Development Lifecycle (SDLC) was observed for software team. Meanwhile, hardware team continuously explored AI in their design work through third party offerings and partnership. Productivity gains and cost savings also became more evident and quick wins get recognized at a faster rate on active projects. The organization structure was also reshaping. Executive level position appointment for Generative AI and ongoing recruitment for AI Engineers to handle dedicated roles for AI work reshaped the new organizational structure. An internal site level committee was also formed with members fulfilling ad-hoc roles on various capacity. Both the AI dedicated team and ad-hoc team members will concurrently implement and expand AI activities. These include Generative AI, Predictive Analytics /Predictive AI, Machine Learning, AI-Driven Automation, Agentic AI for bother Autonomous and Semi-

Autonomous Agents, Decision Intelligence and Augmented Decision-Making AI Tools and AI-Powered Knowledge Systems. Progress on employee behavior and engagement since the study started also shown consistent high engagement among enthusiasts. In fact, employee engagement activities such as AI day were being planned for the year. In AI literacy, a new batch of employees were being trained through best in class offshore based university training in Singapore, sponsored by respective BUs. These trainings will cover more functional groups. As expected, the goals that were given to the first batch of graduates concluded successfully with their capstone completed that were productivity gain focused projects. In alignment to findings and recommendations on organizational policies and ethical consideration, significant progress was seen in this with local AI policy and Do’s and Don’ts Guidelines approved and published to cover gaps on documentation related to ethical and responsible use. The presence and support of the members of the management team during the course of the study has allowed me to maintain regular management alignment. The structured feedback mechanism ensured the end result of the study will be useful and the recommendations that were presented during the course of study identified to be low hanging fruit will be applied immediately as resource and budget permits. I believe both myself and the organization have already benefitted in this research. The topic selected was a clear need to initiate the R&D transformation so it can fulfill the evolving demand and organizational requirement.

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APPENDICES

APPENDIX A

General Instructions

Members of the Technology team affiliated with SYSS Manila are invited to participate in the survey. Upon submission, your name and email address will be recorded in the form. You are requested to share your insights and experiences regarding the adoption of AI at our site.

Please ensure that all questions are answered and that you make appropriate selections for items requiring responses from the available options. For questions with Other, input N/A if not applicable. The survey encompasses questions related to AI adoption and the resulting productivity improvements. For further clarification, please consult the Definition of Terms provided below.

If you have any additional questions or require further assistance, please contact Hershey Catimbang.

Table 1. Detailed Definition of Terms (Microsoft Copilot, 2025)

Terms	**Definition / Description**
AI Literacy	The foundational knowledge and skills required to understand, use, and evaluate artificial intelligence technologies in engineering and business processes.
AI model interpretation	The ability to explain and understand how AI models generate outputs, including the logic, data inputs, and decision pathways.
AI systems	Machine-based systems that infer from input data to generate outputs (predictions, recommendations, decisions) supporting engineering and business objectives.

AI tools	Software or platforms that leverage AI to perform specific tasks such as data analysis, simulation, or process optimization.
Artificial Intelligence (AI)	The field of computer science focused on creating machines and software that simulate human learning, reasoning, and decision-making. It is used to automate complex engineering tasks, optimize hardware design, and support business intelligence.
Classroom type training	Structured, instructor-led sessions (in-person or virtual) for learning technical skills, compliance requirements, or organizational policies.
Conference	Formal gatherings organized by professional societies or industry groups where experts share research, best practices, and innovations.
Customers	Individuals, teams, or organizations who receive products, services, or solutions from SYSS Manila. Customers may be internal (other business units) or external (end-users, partners, or clients).
Data analysis	The systematic process of collecting, cleaning, transforming, and interpreting data to discover useful information, identify patterns, and support decision-making in engineering and operations.
Ethical and responsible use	Adhering to professional codes of conduct and organizational policies to ensure that technology, data, and

	engineering practices are used in ways that protect public safety, privacy, and the environment.
On-the-job training	Practical, hands-on learning conducted in the actual work environment. It is used to develop technical and interpersonal skills, bridge theory and practice, and prepare employees for specific roles or tasks.
Peer-led	Training or learning activities facilitated by colleagues or team members who have expertise in a subject.
Productivity Gains	Increases in output or efficiency achieved through process improvements, automation, technology adoption, or skill development. It is measured in terms of reduced cycle times, increased throughput, and cost savings.
Programming/scripting	The use of programming languages (e.g., Python, C, VHDL, Verilog) and scripting tools to automate tasks, analyze data, and develop hardware/software solutions.
Prompt engineering	The process of designing and refining inputs (prompts) for AI tools to produce specific, high-quality outputs. It is used to optimize interactions with generative AI models, improve productivity, and support technical workflows.
Self-instructed training	Learning that is initiated and managed by the individual, often using online resources, manuals, or self-paced modules.

Survey Form

Demographics and Role

1. What is your role within your team?
    - Software Engineering
    - Hardware Engineering
    - Test Engineering
    - Management
    - Other (please specify)

0. How long have you been working in our company?
    - Less than 1 year
    - 1-5 years
    - 6-10 years
    - More than 10 years

0. What are the main challenges you face in adopting AI in your work?

1. Any suggestions on how the current challenges can be addressed?

2. What changes would you suggest to improve AI adoption in our organization?

AI Literacy

3. Please rate your AI proficiency in the following areas (1 – Low, 5 – High)

	1 – Low	2	3	4	5 - High
Data Analysis					
Programming/Scripting					
AI model interpretation					
Prompt engineering					
Collaboration and communication					
Ethical and responsible use					

4. What format of training on AI tools and concepts have you received (Select all that applies)?
    - Self-instructed
    - Classroom type
    - On-the-job training
    - Peer-led
    - Conference
    - Other
5. Please provide titles of AI trainings you've attended?
6. Describe how your skills have helped you in applying AU at work.
7. Describe how your skills have hindered you in applying AI at work?
8. What else do you think are required in terms of AI literacy to enhance productivity?

Organizational Structure

9. How effective do you feel our organization is at supporting AI Adoption based on each area (1 – Ineffective, 5 – Effective)?

	Very Effective	Somewhat Effective	Neither effective or ineffective	Somewhat ineffective	Very Ineffective
Software Tool Needs					
Hardware Requirements					
Training Needs					
Management on AI Direction and Strategy					

AI Governance, Policies and Ethical Use					
Incentives and Rewards on AI Initiatives					

10. What else do you think are required in terms of organizational structure to enhance productivity?

Employee Engagement and Behavior

11. How effective is the communication about AI Adoption programs between employees and management (1 – Ineffective, 5 – Effective)?
12. How effective is the communication about AI adoption programs with customers (1 – Ineffective, 5 – Effective)?
13. What motivates you to adopt AI at work?
14. What else do you think are required in terms of employee engagement and behavior to enhance productivity?

Organizational Policies and Ethical Consideration

15. What problems do you encounter when implementing AI tools or systems in your organization?
16. How are you informed or trained about the ethical use of AI in your role?
17. What else do you think are required in terms of organizational policies and ethical use to enhance productivity?

Impact and Outcome

18. How has AI impacted your productivity gains in fulfilling project deliverables or software or hardware development outputs?

19. What are the areas do you think the use of AI could have improved organizational productivity? Can you give specific examples?
20. What improvements would you suggest to increase AI adoption success in your team?

APPENDIX B

Interview Questions

R&D Organizational Structure

1. How is AI integration currently structured within your team or department?
2. Can you describe any dedicated roles, committees, or cross-functional groups focused on AI initiatives?
3. How do these structures support AI adoption? How do these structures hinder AI adoption?
4. What changes in the organizational structure do you believe would be most effective in enabling higher AI adoption in your workplace?
5. Are there specific management practices, cross-team collaboration, resource allocations, or leadership actions that could improve alignment and prioritization of AI projects?

AI Literacy

6. What are the most critical AI-related skills or knowledge areas needed in your role?
7. How confident are you in your current proficiency in AI, and what training formats have been most effective for you?
8. How do you and your colleagues typically learn about new AI tools or concepts?
9. What barriers have you encountered in accessing or understanding AI training, and how could these be addressed?
10. How does your team ensure ethical and responsible use of AI in daily work?

11. Are there guidelines or training provided, and do you feel equipped to handle ethical considerations related to AI?

Adoption Experience

12. Can you describe a recent experience where AI was introduced into your workflow?
13. What were the main challenges or successes during this process?
14. What motivates you or your team to adopt AI tools in your projects?
15. Are there specific incentives, recognition, or personal drivers that encourage adoption with AI?
16. What factors have limited the adoption of AI in your team? What factors have accelerated the adoption of AI in your team?
17. How do time constraints, tool compatibility, or management support affect your ability to use AI?

Employee Engagement and Behavior

18. How would you describe the level of engagement with AI among your colleagues?
19. What behaviors or attitudes have you observed that help AI adoption? What behaviors or attitudes have you observed that hinder AI adoption?
20. What role does management play in fostering employee engagement with AI?
21. Are there specific actions, incentives, or recognition that have made a difference? What do you think the management should do in terms of incentives, recognition, others?

Organizational Policies and Ethical Consideration

22. How do organizational policies and approval processes impact your ability to use AI tools?
23. Can you share examples of policy-related challenges or suggestions for improvement?
24. What concerns do you have about data security, privacy, or ethical use of AI in your work?
25. How could the organization better support responsible AI use while enabling innovation?

Impact and Outcome

26. How has AI adoption affected productivity or quality in your design and development work?
27. Can you provide specific examples of tasks or projects where AI made a measurable difference?
28. What do you see as the main benefits and future opportunities of enhancing AI adoption in your R&D environment?
29. Are there areas where broader AI use could have the greatest impact?

APPENDIX C

Confidential AI Adoption Analysis (Confidential)

This appendix contains a detailed AI adoption analysis report related to the company's practices, challenges, and strategic initiatives. Due to the confidential nature of the content, the full document is not included in this manuscript. Access to the analysis can be granted upon request, subject to confidentiality agreements and approval from authorized personnel.