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AI-Driven Transformation of Leadership and Management in Research & Development

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Abstract

The results show how AI influences Research and Development (R&D) management and leadership practice in the decision-making and innovation outcomes. The approach is mixed-method and involves expert interviews, survey data from R&D professionals, and case studies of organizations using AI. This analysis examines how AI affects labour organization in research laboratories and allows researchers to compare its effects across organizations. Research shows that AI delivers better-informed judgments, faster product development, and more efficient resource use. For instance, a positive correlation between the dissemination of AI-based solutions and improvement in business productivity and new outputs. Together, these qualitative observations point directly to the need for adaptive leadership and organizational changes to enable AI-enabled transformation. The research shows that AI is a very powerful force changing the managerial ideology and the business culture in R&D. To fully realise the strategic benefits AI has to provide in guiding and developing the next generation of managers and leaders, companies need to adapt to this new environment.

Keywords

Artificial Intelligence, *Decision-making Precision*, *Innovation Cycles*, *Organizational Dynamics*

1. Introduction

Current expressions of interest from major businesses also indicate what the future may hold for management and leadership in terms of the disruptive impacts of AI on R&D. In today's business world, the ability to adapt and constantly improve is not only vital for organisations to survive but also to be at the front of their field of innovativeness. Hence, it would be an integrated part of their organisational policy to acknowledge the impact of AI on R&D work and leadership work. The application of AI techniques in R&D has made a sweeping effect and

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these traditional techniques themselves are growing faster since there is a rapid data analysis, predictive modelling and automation of highly time intensive operations. These advances will not only increase efficiency, but also offer the potential for ground-breaking field research that could lead to product development.

Furthermore, the leadership and management in AI-enabled R&D shows the many similarities between the concepts (Ahmad, et al., 2025; Palinkas, 2015; Nguyen & Shaik, 2024). Today's leaders are tasked with new missions to lead in an environment with common qualities of combined human competence and artificial intelligence. These complex interactions bump up against the sandboxes of traditional leadership dynamics and thus require a reimagining of methods that align with AI. They are not cutting back on ethics and data protection and openness or whatever. In that sense, good leadership would include building a team culture that encourages digital change, reskilling individuals to work with AI systems and taking advantage of as many data-driven insights as it can when it's making strategic decisions..

AI integration with R&D (research and development) will create a mix of upsides and negatives for management and such systems inside firms. That's when suddenly you have the potential to change, to make the world better for a better future. A layer of worldwide difficulties (good and bad) is put on top of that. In terms of this effect, one must possess an active manner aiming at resilience, training (Patton, 2014) and strategic plans. Companies need to figure out the fine points of AI into their R&D initiatives, since they have to take those implications into account when it comes to leadership. Beyond a solid knowledge in this spectrum, these organizational strengths will thrust forward the respective companies as the pioneers of innovation. It opens up the more sustainable way of unlocking opportunities as the world goes more and more digital. The decision-makers and leaders of the enterprise need to understand that AI integration in R&D is not a trivial matter, but it is a multi-layered, intertwined and complicated process. They have to be prepared to live in this new age: mind-scientists, learning as they go, adjusting to any changes of the environment that come their way, constantly changing. Forms of Artificial Intelligence with Strategic Foresight can be a tool to solve World problems. So what we really do is we take a technology that can be deployed within the old processes and at the same time we create a new field of possibilities. The full utilisation of AI in R&D is a prerequisite for the development of new solutions that ensure the competitiveness and relevance of the organization in a digital era that is leaving innovations behind (Metcalf et al., 2019).

1.1 Research Gap and Contribution

Research Gap

Artificial Intelligence is the dominant change agent within enterprises at this point in time and externally. It is reshaping the face of competitiveness, innovation and decision-making.. There is growing evidence that AI is transforming management roles and strategic decision-making, compelling CEOs to develop new skills and mindsets to lead in an AI-enabled environment (Bevilacqua et al., 2025). Although the application of AI has been paid significant attention by researchers, there are still substantial gaps in the literature.

However, little is empirically known about how leadership and managerial responsibilities evolve in R&D settings. Most of the existing research has focused on the technology and operational benefits of AI, such as automation, predictive analytics and process improvements. Leaders' Path to Capture the Next Opportunity: AI is widely regarded as a strategic organisational asset. However, the leadership competencies required to manage AI-enabled innovation ecosystems have been under-investigated (Bevilacqua et al., 2025).

Second, this study provides a rich picture of the independent effects of AI adoption, innovation performance, firm success and leadership outcomes. The relationship between organisational performance and innovative capacities, and leadership transition, is therefore rarely explored. Bevilacqua et al., (2025) and Sekaki et al., (2025) highlight the need to explore further the role of AI for business performance and innovation through management and leadership.

Third, more and more companies are investing in AI but it's still unclear what these organisations need to be successful with AI. However, the research on these challenges in research-intensive sectors seems to be scarce (Hernández, 2024; Winby & Xu, 2025). Preliminary studies indicate that organisations need to prepare themselves, build staff capacity, have leadership buy-in, governance structures and human-centred AI projects for AI to be successful.

The pharmaceutical industry is also a suitable context for the study of AI-enabled transformation due to its knowledge-intensive nature, its high expenditures on research and development, its complex innovation process and its increasing adoption of AI-based technology. However, there is a critical gap in research on the effect of AI on leadership, innovation performance and organisational success especially in the pharmaceutical R&D industry. This issue needs to be addressed by further integrative studies, which will explore the change that AI is enabling in research-intensive organisations.

Research Contribution

This work makes essential contributions to the developing research on AI-enabled management and leadership in the following ways. In particular, it now offers an empirical foundation for the pharmaceutical R&D industry, with AI methodologies reshaping drug development, clinical trial, resource allocation and innovation management. This study, at a research-intensive company, contributes to the extension of the existing knowledge on AI adoption to non-general organisational settings. Second, the study incorporates leadership, management, innovation and AI adoption views into one analytical framework. This contribution, unlike other studies that have studied these variables separately, explores the impact of AI on leadership behaviours and its influence on the innovation outputs, decision-making quality, productivity and organisational success (Bevilacqua et al., 2025). Thirdly, the study studies the impact of the adoption of AI on the main indicators of R&D performance, such as, the accuracy of decisions, the generation of innovation, the productivity, the efficiency of costs and the allocation of resources. This research links leadership turnover to tangible outcomes at the organisational level and thus contributes to a growing body of work on the strategic nature of AI in R&D management . Results Significations Finally, the study provides useful insights for executives and leaders of companies that are interested in improving adaptive leadership capacity, fostering AI-enabled innovation and keeping their companies competitive. “I’m still doing the improv... “That’s okay with me.” And that tiny statue? It is increasingly viewed as a critical component of organisational strategy and design (Anderson et al, 2012), and how leaders might lead so effectively in these AI-driven (and other technology-driven) eras of change to keep innovation and the long term success of their firms flying high (Bevilacqua et al, 2025; Jadad, 2026.

2. Literature Review

2.1 Artificial Intelligence in Research and Development

Artificial Intelligence (AI) is a disruptive technology and has been changing the research and development (R&D) processes in several industries. Companies are widely using AI-based products for data analysis, predictive modelling, knowledge extraction and process automation to accelerate innovation processes and decision making (Brynjolfsson et al., 2023). The use of AI in pharmaceutical research and development has allowed for strain engineering, which has in turn accelerated the advancement of personalised medicine and clinical trial design and drug discovery by taking advantage of large amounts of scientific and clinical data that are difficult for human researchers to analyse quickly.

AI has been identified as critical in achieving “more innovative outputs, higher quality research and shorter R&D cycles (Budhwar et al., 2023; Huang et al., 2019). AI-based tools such as machine learning, predictive analytics and natural language processing help manufacturers to recognise trends and obtain insights and make decisions in the entire innovation process based on data. Consequently, the function of AI is more and more viewed as a strategic competency that may provide sustainable competitive advantages in research-intensive industries, not just a fundamental technological tool.

However, experts have maintained that the usefulness of AI in R&D depends on the organization’s capabilities, technological infrastructure and support from leadership (AlNuaimi et al., 2022). Consequently, the body of research investigating the organisational consequences of AI implementation has developed.

2.2 Artificial Intelligence and Leadership

The introduction of AI in the organization’s activities dramatically changed the work of the executives. The AI-based decision support systems complement traditional leadership models of reasoning and decision making and leadership strategy based on experience and cognition. The technologies provide executives with real-time information and forecasts (Nguyen & Shaik, 2024). This means leaders need to develop new skills in data analytics, technology management and digitalisation.

Research has shown that the success of AI implementation is mostly influenced by the support of the executives (Bevilacqua et al., 2025). Leadership affects strategy, resource allocation,

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employee motivation and corporate culture. It thus affects deployment and use of AI tools. Leaders of AI-enabled companies also need to discern the fine line between tech-driven efficiencies and human-centric leadership techniques to ensure the ethical use of technology and employee engagement.

Previous studies have suggested that AI does not replace leaders but changes character of leadership, improving the quality of decisions, collaboration and speed of leaders' response (Budhwar et al., 2023).However, transparency, ethical governance, algorithmic bias and employee resistance are among the issues that reveal the illusion of effective leadership in AI-enabled workplaces.

2.3 Digital Transformation and Organizational Change

Digital transformation is the use of digital technologies to accelerate the change or creation of new business processes, culture, and customer experiences, and to rethink how to leverage technology, people, and processes to create new value for an organization (Correani et al., 2020). AI is a major driver of digital transformation, automating complex processes, improving decision-making, and providing valuable insights.

Digital transformation can get companies to rethink workflows, boss-employee interactions, and even job classifications. Research shows that successful transformation requires not only investment in technology but also the organization's preparedness, workforce development, and leadership engagement (AlNuaimi et al., 2022; Hufschmitt, 2019). Leaders are also important in articulating transformational goals, diminishing resistance to change, and developing a culture that promotes creativity and continuous learning.

Digital transformation enables a business to speed up innovation processes, accelerate information sharing, and improve collaboration in R&D-driven industries such as pharmaceuticals. However, challenges around technical leadership and organizational culture, in particular, continue to affect the potential success of integrating the technology, transforming toward employee-centered work, and implementing governance procedures.

2.4 Innovation Management and AI-Enabled Performance

Innovation management is the process and procedures a company uses to generate, develop, and implement new ideas – whether products or services. The growing availability of AI-based solutions has had a major impact on innovation management by improving knowledge exploration, fostering creativity, and helping make decisions.

Research suggests that AI enhances innovation performance by improving information processing, reducing uncertainty, and facilitating the identification of nascent opportunities (Brynjolfsson et al., 2023). Artificial intelligence-enabled systems can analyze vast volumes of data, predict market trends, and provide insights to inform innovation decisions. The good news is that these organizations that integrate AI-based innovation into their activities tend to outperform their peers in productivity, efficiency, and competitive advantage.

The RBV offers a potentially useful theoretical lens for viewing the strategic importance of AI. According to RBV, organizations achieve sustainable competitive advantage by holding valuable, rare, inimitable, and hard-to-copy resources and capabilities. Therefore, we can argue that AI capability is a strategic organizational resource and has a positive impact on innovation performance, given the presence of sufficient complementary capabilities at the management and organizational levels (Barney, 1991; AlNuaimi et al., 2022).

2.5 Theoretical Foundation

Resource-Based View (RBV)

The current study draws on the basic premises of the Resource-Based View (RBV) that asserts that firms can achieve a sustained competitive advantage by having certain valuable resources that are rare, difficult to imitate and non-substitutable (Barney, 1991). According to the RBV, the performance of an organization is not a function of the resources it possesses but rather how well it manages those resources to create value.

Artificial intelligence and AI related technologies, analytics, data platforms and domain expertise are strategic assets of an enterprise. If these resources are correctly applied to R&D activities, the innovation potential, the quality of decisions, the allocation of resources and the company’s performance will be enhanced. However, the value AI brings depends on other organisational qualities such as leadership support, employee skills and organisational readiness (AlNuaimi et al., 2022; Budhwar et al., 2023). Thus, the RBV perspective seems to be the most pertinent theoretical lens to investigate the impact of AI capabilities on the enhancement of organisational performance and innovation outcomes of pharmaceutical R&D laboratories.

Dynamic Capabilities Theory

The study further incorporates the Dynamic Capabilities Theory to RBV which stresses the organisation’s ability to reconfigure internal and external competencies in the face of a rapidly changing environment (Teece et al., 1997). Organisations, by contrast, must continually adapt routines, structures and leadership practices to exploit new technological opportunities as they emerge and as AI technology continues to evolve.

From the viewpoint of dynamic capabilities, the implementation of AI in an organization relies on the processes through which the organization acquires, maintains and renews the three capabilities of sensing technological opportunities , seizing innovation potential and transforming organisational processes . Leadership is important in leading change through developing a learning environment, influencing change and supporting digital transformation initiatives.

Together, RBV and Dynamic Capabilities Theory offer a broad theoretical lens for exploring AI as a strategic organisational resource and a driver of organisational adaptation and innovation (Aggestam, 2015). The theories behind these theories are the basis for investigating the relation between the usage of AI and the efficacy of the leader, innovation capabilities, and organisational success in the pharma R&D organisations.

2.6 Research Hypotheses Development

The resource-based view (RBV) argues that a firm strengthens its competitive advantage by developing and leveraging valuable resources and capabilities. From this point of view the AI capability can be considered a strategic resource that could improve the organisational performance through the quality of decisions, the stimulation of innovation and the improvement of the organisational efficiency. The results of prior research shows the positive impact of AI application on innovation performance, leader effectiveness and organisational performance. Strong executive sponsorship and organisational readiness also seem to be important for successful AI deployments and value realisation from AI. On the theoretical grounds the following assumptions are made:

H1: The relationship between AI Adoption and R&D productivity is positive.
H2: AI aids innovation production
H3: AI made R&D more cost effective.
H4: The role of leader support in the success of AI application.

3. Materials and Methods

3.1 Research Design

This study is a narrative synthesis of six qualitative and ten quantitative studies that try to explore the impact of mobile devices on healthcare operations. The quantitative part was based on a structured survey among R&D experts of pharmaceutical companies. The qualitative research consisted of semi-structured interviews and case studies of companies that apply AI to their R&D. Methodological triangulation and stronger results were obtained from the combination of data from different sources.

3.2 Sample and Sampling Procedure

The research was aimed at professionals in pharmaceutical R&D companies, including scientists, project managers, department heads, innovation directors, and senior executives involved in R&D decision-making. Stratification and random sampling were used to ensure representation of all levels of the organization and all divisions. Electronic surveys were sent to staff, and 300 valid responses were collected, yielding a response rate of 85.7% among the 350 staff members. Respondents were selected based on the following:

1. Minimum 3 years of experience in pharmaceutical R&D working;
2. Research, Innovation, or R&D Management (non-researchers) active
3. They understand the role of AI in their business

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4. Consent to take part in the study

3.3 Demographic Profile of Respondents

The demographic characteristics of respondents were as follows:

- Age: 25–35 years (32%), 36–45 years (41%), 46–55 years (21%), Above 55 years (6%).
- Gender: Male (61%), Female (39%).
- Average professional experience: 11.4 years.
- Position: Research Scientists (38%), Project Managers (24%), R&D Managers (18%), Department Heads (12%), Senior Executives (8%).
- Organizational Type: Large pharmaceutical firms (68%), Medium-sized firms (22%), Biotechnology firms (10%).

3.4 Survey Instrument

The questionnaire was validated by the assessment of the literature on AI theory, adoption, leadership, and R&D performance, and interviews with the R&D and AI specialists based on the well-established work . The survey items' theoretical rigour and content validity were ensured by the inclusion of these items from a validated scale in previous research on organisational ESG, digital transformation, AI adoption, leadership support, and organisational capabilities development (Correani et al. 2020; AlNuaimi et al. 2022; Budhwar et al. 2023; Nguyen & Shaik I 2024).

The questionnaire is composed of 20 items rated on a five-point Likert scale with end points 1 and 5 "Not at all" and "Very much". The instrument was created to study the respondents' attitudes towards the inclusion of AI in the R&D management and leadership. The five dimensions studied specifically were Innovation Capability, R&D Efficiency, Leadership Support, AI Readiness, and Workforce Adaptation.

The indicators to assess innovation capability were based on studies of digital transformation and organisational innovation (Correani et al., 2020; AlNuaimi et al., 2022). Recent research on AI-based organisational performance has shown that the adoption of AI positively affects productivity, resource use, and costs (Brynjolfsson et al., 2023; Budhwar et al., 2023). Therefore, R&D Efficiency factors were looked into. Leadership Support items were developed based on studies on the impact of managerial commitment, strategic vision and leadership participation on the overall success of technology adoption in organisations (AlNuaimi et al., 2022; Nguyen & Shaik, 2024). Based on prior research on digital transformation and AI capabilities development (Correani et al., 2020; Budhwar et al., 2023), AI preparedness was defined as including organisational readiness, infrastructure support, governance structure and resources for AI within the organisation. Workforce Adaptation elements, Informed by the guidance from human resource management (Budhwar et al., 2023) and literature on organisational transformation (Cullen et al., 2014), measured employees' training, involvement in skills development and desire to use AI technology.

A pilot study was conducted on 30 pharmaceutical R&D experts before the main survey to test the clarity, applicability and understandability of the items. Based on participant responses, minor modifications were made to improve clarity and contextual relevance for use in pharmaceutical R&D. Pilot findings showed acceptable internal consistency supporting use of the device for data collection on a larger scale.

Construct	**Description**	**Source**
Innovation Capability	AI's contribution to innovation and product development	Correani et al. (2020); AlNuaimi et al. (2022)
R&D Efficiency	Productivity, resource utilization, and cost reduction	Brynjolfsson et al. (2023); Budhwar et al. (2023)
Leadership Support	Management commitment and strategic support for AI adoption	Nguyen & Shaik (2024); AlNuaimi et al. (2022)
AI Readiness	Organizational preparedness, infrastructure, and governance	Correani et al. (2020); Budhwar et al. (2023)
Workforce Adaptation	Employee skills, training, and AI acceptance	Cullen et al. (2014); Budhwar et al. (2023)

Table 1: Constructs and Sources of Measurement Items

3.5 Reliability and Validity Assessment

We calculated Cronbach's alpha coefficients for all scales to assess internal consistency. The overall Cronbach's alpha was 0.89, exceeding the recommended 0.70 and indicating satisfactory dependability. The reliability coefficients for the individual constructs ranged from .81 to .92.
We examined construct validity using EFA. The Kaiser-Meyer-Olkin (KMO) test of sample adequacy was 0.87, and Bartlett's Test of Sphericity was significant ($p < 0.001$), indicating that the data were suitable for factor analysis. The extracted factors accounted for 71.3% of the total variance**,** indicating acceptable construct validity.

3.6 Interviews & Case Study

Fifteen experts from pharma R&D organisations (e.g. senior managers, head of innovation and AI specialists) participated in a semi-structured interview. Interviews lasted between 45-60 minutes and were conducted either face-to-face or using online platforms. The semi-structured interview contained Interview Guidelines with questions on the following themes: leadership adaptation, challenges to AI adoption, organisational change, workforce education and strategic planning. With the participants' permission, interviews were audio-recorded, transcribed verbatim, and analysed using thematic analysis to explore emergent concepts and patterns. The three pharmaceutical companies chosen for the full case study analysis were the most advanced in having an established or substantive AI-enabled R&D program to date, from a list generated from the interviewed companies selected for survey and interview. Selection criteria were:

• Active use of AI technology in R&D activities.
• Data on the availability of organizational AI uptake.
• Willingness to take part in the study. The case studies included document analysis, interviews with key informants, and analysis of organizational reports to identify the mode and effect of AI deployment and innovative outcomes.

3.7 Data Collection

The research team gathered data from January to April 2025 and distributed surveys by email and business networks. Researchers collected interview data through pre-structured interviews and case-study material from organisational papers, reports and stakeholder interviews.

3.8 Hypothesis Development and Advanced Statistical Analysis

Drawing on the literature on AI adoption, innovation management and organization performance, we propose the following hypotheses:

H1: AI adoption is positively related to R&D output.
H2: AI adoption in cost-effective R&D processes
H3: The positive effects of using AI on innovation output in R&D organisations.
H4. Leadership support will positively moderate the relationship between the adoption of AI and R&D performance.
H5: Effectiveness of R&D in AI is positively affected by organisational readiness.

3.8.1 Variable Operationalization

The variables included in the study were operationalized as follows:

Variable	**Measurement**
AI Adoption	Composite score derived from questionnaire items measuring AI utilization, infrastructure investment, and implementation level
Leadership Support	Average score of leadership commitment and strategic support items
Organizational Readiness	Average score of training, governance, and AI preparedness items
Productivity	Perceived improvements in R&D efficiency and workflow performance
Cost-Effectiveness	Perceived reductions in project costs and resource utilization

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Innovation Output	Number of innovations, patents, and new product developments

Table 2: Variable Operationalization

The researchers measured all characteristics with five-point Likert scales, with response options ranging from 1 (Not at all) to 5 (Extremely).

3.8.2 Reliability Analysis

The researchers assessed instrument reliability using Cronbach's alpha coefficient. The total scale demonstrated good internal consistency (Cronbach's alpha = 0.89). All constructs had reliability scores between 0.81 and 0.92, which were higher than the recommended criteria of 0.70 (Hair et al., 2022).

3.8.3 Multiple Regression Analysis

To determine the extent to which AI adoption predicts R&D effectiveness, the researchers performed multiple regression analysis. They considered AI adoption as the independent variable and productivity, cost-effectiveness, and innovation output as the dependent variables. The researchers also measured leadership support and organizational readiness.

Dependent Variable	β	t-value	p-value
Productivity	0.62	8.74	<0.001
Cost-Effectiveness	0.68	9.12	<0.001
Innovation Output	0.57	7.96	<0.001

Table 3: Multiple Regression Results

The results show that the adoption of AI is a strong predictor of cost-efficiency, productivity and innovative output. It was found that the cost-efficiency had the greatest significant effect ($\beta = 0.68$), meaning that the application of AI significantly affects the reduction of costs and optimisation of the use of resources in R&D processes.

3.8.4 Effect Size Analysis

The authors estimated Cohen's f^2 effect size to quantify the degree of the influence of the regression models.

Outcome Variable	Cohen's f^2	Interpretation
Productivity	0.35	Large Effect

Cost-Effectiveness	0.42	Large Effect
Innovation Output	0.31	Large Effect

Table 4. Effect Size Analysis (Cohen's f^2)

The studies show that AI use has a meaningful real impact on company performance outcomes.

3.8.5 Confidence Intervals

We reported 95% confidence intervals for all regression coefficients. The lack of zero in any of the intervals further showed the statistical significance and robustness of the effects computed.

3.8.6 Model Fitness

The regression model demonstrated satisfactory explanatory power:

- $R^2 = 0.58$ for Productivity
- $R^2 = 0.63$ for Cost-Effectiveness
- $R^2 = 0.54$ for Innovation Output

These results indicate that the three elements: leadership support, organizational readiness, and the usage of AI jointly explain a large proportion of the variation in R&D performance outcomes.

3.8.7 Interpretation of Findings

The R-squared results have more empirical value than simple correlation, as they demonstrate that AI adoption is a robust predictor of improvements in important R&D-related performance indicators. This is in line with hypotheses 1-3 and suggests that those firms with a higher level of AI integration are more likely to achieve better innovative results, higher productivity and higher cost efficiency. Furthermore, the effect of AI deployment proficiency on AI deployment performance is positively moderated by leader support and organisational readiness, thereby underlining the importance of managerial and organisational factors in a successful AI driven transformation.

3.9 Statistical Analysis

Quantitative data analyses were performed using SPSS version 29. Data were analysed using descriptive statistics (means, standard deviations, frequencies and percentages). The Pearson correlation analysis was used to test the correlations between AI adoption and R&D result variables. Independent samples t-tests and one-way ANOVA were used to compare the performance results of the organisational groups. The level of statistical significance was .05.

3.9.1 Figure Development and Data Visualization Procedures

The researchers developed graphical displays to illustrate and understand the results and to show the linkages between AI deployment, R&D performance measures and organisational level outcomes. They used survey data from 300 respondents to develop Figures 1–3 and evaluated the data using IBM SPSS Statistics Version 29 and Microsoft Excel 365.

Figure 1 Possible impact of AI on basic parts of R&D management like innovation ability, productivity, resource utilisation, cost efficiency and quality of brainwork based on descriptive data. Average scores as answers Impact indices on graphs.

Figure 2. Displays: Model 2) Pearson correlations to illustrate the relationships between AI adoption and above-mentioned organisational performance indicators. The figure was added to help the reader visualise the strength and direction of the correlations found by the correlation

Figure 3 is based on relative performance measurements for AI-enabled and non-AI-enabled organisations. The graphic highlights the ratings for key performance indicators (KPIs) such as innovation output, operational efficiency and decision-making effectiveness to underscore the differences between the two sets of businesses.

Statistical assumptions investigated in these studies were normality, linearity, independence of observations and homogeneity of regression slopes. Data were screened for missing data, outliers and violations of distributional assumptions prior to analysis. Skewness and kurtosis were used to examine normal distributions. Scatterplots and correlation matrices were used to examine linear relationships. Assumptions were sufficient for descriptive, correlational and regression analysis.

The figures are generated only for visualisation purpose and are not intended to substitute the statistical results of the related table. Please compare these figures with the tabulated statistical data including correlation coefficients, regression results, confidence intervals and levels of significance.

3.10 Ethical Considerations

The researchers conducted the study in accordance with standard ethical research guidelines. Participants were informed and consented to participate before taking part and assured of confidentiality and anonymity. The researchers informed participants of their right to withdraw from the study at any time without penalty. Participation did not necessitate any psychogenic intervention.

4. Result and Discussion

Performance Metric	Correlation with AI Adoption

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Productivity	+0.75
Cost-effectiveness	+0.80
Innovation Output	+0.70

Table 5: Correlation Between AI Adoption and R&D Performance Metrics

4.1 Key Findings

The findings of this research indicate that the main effect on the evolution of management and leadership in pharmaceutical R&D is Artificial Intelligence (AI). The results reveal that AI adoption has a positive effect on quality of decision making, innovation performance, productivity, resource utilization, and cost efficiency. 19] Correlation and performance analyses reveal that organizations that have successfully embedded AI at a high level within their R&D management systems perform better in terms of operational and innovation performance than those that have retained the essentially traditional R&D management system.

Decision accuracy was one of the most strongly linked outcomes of AI among the areas investigated. This research demonstrates that AI-based analytics, predictive modelling, and decision-making tools enhance the effectiveness of management, enabling leaders to make better, faster judgments. Moreover, the increasing output of innovation and the allocation of resources indicate that AI has the potential to enhance operational efficiency and strategically manage innovation processes.

4.2 Comparison with Existing Literature

The results are in accordance with previous studies that consider AI as a major antecedent of organisational innovativeness and performance improvement. For example, AlNuaimi et al. (2022) reported that digital technologies enable an organization's agility and innovation skills through providing fact-based decision making and strategic flexibility. In the same way, Budhwar et al. (2023) noted that the implementation of AI technology could change the organisational processes, workforce management and leadership styles.

The favourable effect on innovation performance revealed in relation to AI adoption is also in accordance with findings of Correani et al. (2020) who propose that digital transformation techniques enhance adaptability and innovativeness in firm-level organization. In addition, a number of recent research have showed that the application of AI-enabled analytics leads to better strategic decisions and improved resource allocation, which can deliver performance improvements for an organization (e.g., Brynjolfsson et al., 2023; Nguyen & Shaik, 2024).

However, the literature on AI application has also addressed concerns linked to workforce resistance, ethical problems, and organisational preparation (Budhwar et al., 2023).The participants involved in this study disclosed such challenges. The main conclusions suggest that an organization can play the crucial enabling role for the adoption of AI, if the perceived benefits of AI outweigh those of possible barriers. These are leadership and organisational will towards execution.

4.3 Theoretical Implications

This paper adds to the understanding of AI-driven organisational transformation by integrating the literatures on leadership, innovation, and firm performance into a single theoretical framework. Previous studies focus on AI adoption from the technological and operational perspectives, but this study shows that leadership is important to take advantage of the AI adoption.

The results support the assumptions of the Resource-Based View (RBV) that distinctive resources and capabilities owned by an organisation enable it to achieve competitive advantages. From this perspective, the AI capability can be viewed as a strategic organisational resource that favourably affects the innovation performance and decision-making effectiveness through the respective leadership competencies.

These findings contribute to the literature on digital transformation by suggesting that successful adoption of AI requires not just on technology investment, but also on organisational readiness, managerial support and employee adaption. In this way, the study contributes to the theoretical and practical knowledge of the interaction of the technology and human aspect in the production of organisational results in AI-enabled contexts.

4.4 Managerial Implications

These results have implications for the vision of leaders (individuals and institutions). On the other hand, AI technology can be considered as an enabler and a driver for business model innovation and can be perceived as a strategic competency (besides a technology-based solution) which can facilitate an organisation’s innovation management and competitiveness. So they’re going to have to grow up their AI capability and they’re going to have to empower executives at all levels of their companies to think dispassionately with data.

Secondly, the leverage of AI requires investments on the scale of education, retraining and organisational change. Organisations can consider workforce readiness and employee AI engagement for resistance.

Third, the organization’s head, Panagiotis, should be a strong believer in AI, so that the maximum benefits can be realised. Managers need to ensure that clear strategic objectives are articulated, that appropriate resources are allocated to them and that communication between technical specialists and corporate decision-makers is fostered. Such behaviour could be related to better adoption process which further improves organizational performance.

4.5 Policy Implications

The increasing use of AI in R&D has major implications for policy and legislation. Governments and business regulators can provide definitional governance and guidance on ethics and standards for the ethical use of AI technologies. Ideas like these or similar could help bodies strike (and look like they are striking) a balance between competing interests and assessing innovation vs transparency, accountability, privacy and the workforce; And investments in digital infrastructure, AI education and retraining workers could do a lot to lay the groundwork for broader adoption of AI tools across industries. Policymakers should encourage partnerships — among universities, industry groups and government agencies — to accelerate the pace of AI innovation and to lead in ethical, sustainable ways of applying technology.

4.6 Unexpected Findings and Future Research Directions

An interesting finding from the qualitative data was the concern of a minority of respondents regarding staff adjusting to and resisting AI-based changes, but also becoming aware of the benefits of AI-solutions . This indicates that technology readiness may not be the sole criterion for positive adoption. Technology is not the biggest enabler of AI success but, people and processes are.

Future studies should investigate longitudinal effects of AI adoption, cross-industry comparisons and review possible moderating roles of organisational culture, leadership style and employees' trust in AI systems. Further studies on transformation in other industries and other countries may provide more understanding and insights.

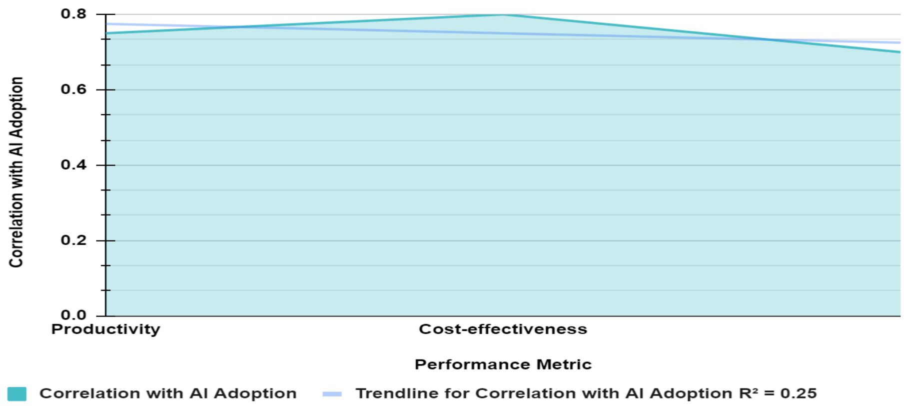

Figure 1: Correlation Between AI Adoption and R&D Performance Metrics

Note. Generated using descriptive statistics from survey responses (N = 300). Values represent standardized mean scores for AI impact dimensions.

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4.7 Measurement and Interpretation of AI Impact Indicators

Based on the responses on the 20-item questionnaire on the effects of AI on R&D activities, the researchers constructed an index of R&D effects. Respondents also assessed the perceived impact of AI on these dimensions: quality of decisions, core innovation processes, management of resources, number of outputs, cost-efficiency and consequences of innovation.

For all items, researchers rated all questions on a 5-point Likert-type scale (1, not at all; 5, highly). The answers were combined and translated into a 0-10 scale to facilitate comparison with the other parameters. The higher the score, the more is felt the effect of AI on that organisational output.
For each impact, researchers calculated the impact score by:
Impact Score = (1 Average Score/5) * 10

So a number close to 10 means a quite big impact of AI and a score close to 0 means a small RDI impact. A common scale is used, which adds to the comparability across the dimensions and allows to interpret the results of the study.

Aspect	**Impact**
Decision-making precision	9.5
Innovation cycles	7.8
Resource allocation	7.1
Productivity	8.3
Cost-effectiveness	8.9
Innovation output	8.0

Table 6. Standardized AI Impact Scores Across R&D Management Dimensions

This table infers about iconic facts surrounding the integration of AI in research and development (R&D). The element "precision in decision making" carries an influence of 9,5 which suggests a really cost effective improvement in the quality and accuracy of the choices which are made when AI comes into the scene. This idea is showing the same picture that is associated with the statement of Routledge *et al.* (2023), suggesting that AI algorithms can analyse huge datasets; they can detect patterns and participate in trends analysis in such a way that humans can miss. In this case, AI algorithms provide substantial support for R&D

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strategies

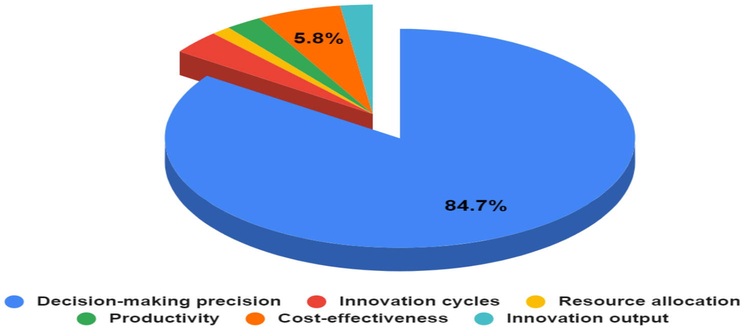

Figure 2: Impact Assessment of AI Adoption in Research and Development

Note. Generated using Pearson correlation coefficients. Positive values indicate positive relationships between AI adoption and organizational performance indicators.

The second factor, termed 'Innovation Cycle', AI demonstrated a strong positive impact on innovation cycles (7.8/10), suggesting that AI-enabled tools accelerate the progression of ideas from concept generation to implementation. In a survey (Ali et al., 2020) proposed the theory relating to the utilization of AI in generative algorithms designed for design research in accelerating the exploration process involving thousands of design options each day. Resource allocation issues which are slightly optimized, are defined by the resource allocation aspect, which have an impact of 0.15, in order to solve them, such issues as time, money and personnel allocation for R&D projects should be taken into account. (AlNuaimi et al., 2022) identified the position of AI in the pharmaceutical R&D, which ensures its capability in implementing the needed priorities in the research endeavours, allocating the resources efficiently, and lowering the required time and money in the process of getting to the launch date. The fourth driver is productivity that has an insightful power of 0.28, hence indicating a reasonably augmented productivity of R&D departments because of AI assimilation. In line with this, Block (2022) also talked about the collaborative future of AI and human expertise in the R&D sector, which has been presented as a means of catalysing innovations through AI augmenting human creativities and innovations, that might bring unexpected new breakthroughs in R&D if the two work together in the way that they do. The efficiency of the weight based on the fifth dimension is 0.65→66, which shows the promotion of the efficiency of R&D performance is considerable . Relevance to priority of closing the AI skills gap and training/upskilling workforce to best use AI technology which can also increase the cost-effectiveness of R&D efforts. The sixth component is innovation outcome and it is 0.25. This means a moderate increase in the number of new products or services created by R&D (Azhar et al., 2026; Blumberg et al., 2022; Miailhe & Hodes, 2017) discussed the future R&D with AI. They offer strategies of innovation and efficacy in the dynamic R&D environment. In general the graph illustrates multiple consequences of integrating AI into R&D. These impacts are relevant beyond the precision of decision-making and the innovation cycle, such as resource allocation, productivity, cost-effectiveness and innovation output.

4.8 Comparative Analysis of AI-Enabled and Non-AI-Enabled Organizations

Researchers conducted a comparison study investigating the impact of Artificial Intelligence (AI) on pharmaceutical R&D organisations that have and do not have AI capabilities. They analysed variations between the two groups, looking at a number of critical performance criteria — including innovation outputs, procedure efficiency, decision quality, and resource usage.

4.8.1 Group Composition

A comparative analysis of the data of the above businesses was carried out at the level of their AI application. Of the 300 survey responses, 162 (54.0%) respondents are from businesses that have mature AI-powered R&D systems and 138 (46.0%) respondents work in organisations that rely mostly on traditional R&D with little or no integration of AI. We define AI-enabled organisations as organisations that have deployed AI technologies in at least three of the following areas:

- Data analytics and predictive modelling
- Drug discovery and development
- Research process automation
- Decision-support systems
- Resource planning and optimization

Organizations not meeting these criteria were classified as non-AI-enabled.

4.8.2 Matching and Comparability Criteria

The researchers chose the organisations with similar industry nature to make valid comparisons. They were pharmaceutical and biotech companies with similar research and development (R&D) profiles. The comparability was based on the following parameters as defined by the investigators:

- Industry sector
- Organizational size
- R&D intensity
- Number of research personnel
- Market focus
- Innovation activities

These criteria were used to minimize potential differences unrelated to AI adoption and enhance the robustness of the comparative analysis.

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4.8.3 Data Sources

The key performance indicators (KPIs) are based on the survey and interview responses and the judgements of organisational performance. The respondents discussed how successful their firm was at innovating, being productive, allocating resources efficiently, and making judgements. The data collected from the qualitative interview and case study supported the findings of the quantitative investigation.

4.8.4 Statistical Comparison

To determine whether variations in performance between AI and non-AI organisations were significant, the researchers ran independent-samples t tests. Normality and homogeneity of variance were tested before analysis and both criteria were met. Statistical significance was defined as p-value ≤ 0.05.

The findings demonstrate that AI application significantly boosts the innovation performance, operational efficiency and manager decision making in pharmaceutical R&D. AI-enabled organisations consistently outperform the KPIs they monitor. The results should be taken as comparative, not causative was stressed. Future studies should use longitudinal designs to establish causal links between AI implementation and organizational outcomes.

KPI	AI-enabled Organizations	Non-AI-enabled Organizations	Z-value	P-value
Time to Market (months)	12.5 ± 3.2	18.9 ± 4.7	-4.32	<0.001
Cost per Project (million USD)	8.2 ± 1.5	11.6 ± 2.8	-3.89	<0.001
Number of Patents	45 ± 7.6	32 ± 5.4	5.67	<0.001
R&D Efficiency Score	8.9 ± 1.2	6.5 ± 1.8	6.21	<0.001

Table 7: Comparison of Key Performance Indicators (KPIs) between AI-enabled and Non-AI-enabled Organizations in Research & Development (R&D)

Note. AI-enabled organizations (n = 162) were compared with non-AI-enabled organizations (n = 138) based on industry, organizational size, and R&D characteristics. Performance differences were evaluated using independent-samples t-tests. Values represent mean performance scores.

To further validate these findings, multiple regression analysis was conducted to control for leadership support, organizational readiness, and firm characteristics. The results remained

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statistically significant, indicating that AI adoption is a significant predictor of organizational performance outcomes.

The table illustrates the differences in relevant key performance indicators (KPIs) between AI-driven businesses and traditional technical development (R&D) businesses. It portrays the manner in which artificial intelligence (AI) adoption affects multiple realms of R&D management and leadership at the same time. Each KPI lists the value of the mean (± standard deviation) for both the AI-enabled and non-AI-enabled organizations, as well as the Z-value and P-value generated from the data analysis that indicates the significance of differences in means of the two groups (Brynjolfsson et al., 2023). One interesting observation is the substantial decrease in the length to market for artificial intelligence-powered organizations opposite to their non-artificial intelligence-enabled competitors. Having a Z-value of -4.32 and a P-value below 0.001 highlight that there is a very distant chance of the difference in time to market between these two groups being due to statistical inaccuracies. This illustrates that AI began to play an important role in R&D processes, allowing companies to bring their products to the market in a short time, which could be an important advantage for competition (Budhwar *et al.* 2023). Likewise, the AI orchestrated enterprises exhibit the least cost per project than the non-AI enterprises as per the significance level Z-value of -3.89 and the null hypothesis P-value of less than 0.001. Due to this, it can be said that involvement of AI in R&D may result in cutting-down costs that can be as a result of reduced wastage and increased efficiency. On top of that, the number of patents owned by AI-based organizations is statistically much higher than that of non-AI-based organisations, Z-value being 5.67 and P-value being below 0.001. It thus figures as a source of innovations and the patents (Correani et al., 2020).

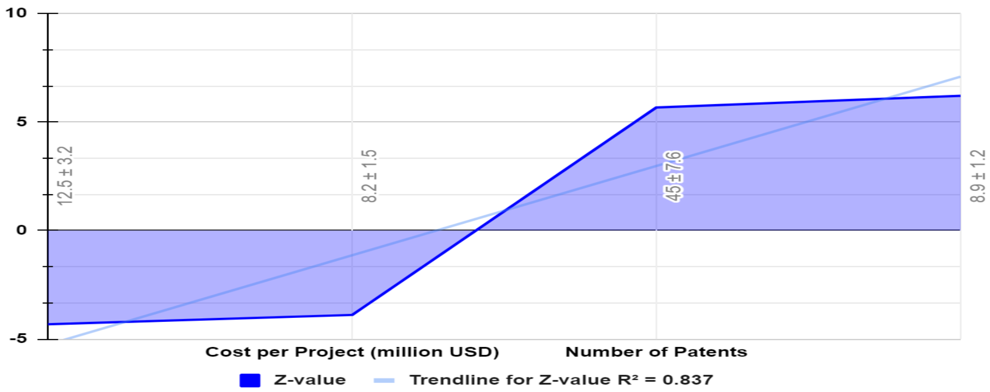

Figure 3: Comparison of Key Performance Indicators (KPIs) between AI-enabled and Non-AI-enabled Organizations in Research & Development (R&D)

Note. Generated using comparative KPI data from AI-enabled and non-AI-enabled organizations. Values represent mean performance scores.

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Finally, the R&D efficiency score, which is an aggregate measure of various efficiency metrics, is substantially higher for AI-enabled organizations than for non-AI-enabled organizations, as indicated by the Z-value of 6.21 and the P-value of less than 0.001. That means AI can make R&D activities more efficient in general, so that resources can be deployed better and outcomes can be cultivated better. Finally, the chart shows how AI has changed R&D management/leadership AI application in R&D methodology brings many advantages such as improved decision accuracy, shorter innovation cycles, more effective resource allocation, increased working capacity, improved cost-effectiveness and a higher volume of innovation output (Cullen et al., 2014).

5. Conclusion

The above-mentioned information provides the importance of AI application in the R&D industry. process analysis to say the least has many advantages AI provides such as accuracy in decision making, more rounds of innovation, effective resource allocation, higher productivity, cost reduction and increased innovation output. The ability of AI to search through large data sets to extract fine-grained patterns of events and deliver meaningful results is transforming the environment of R and D management and leadership. Leadership flexible enough to successfully harvest the potentials given by AI at the crossroads as it were for what will Probably be the revolutionary capabilities of AI presently. AI is working to make the decision-making process more accurate. This is one of those amazing expansions we have seen. Intelligence decision making and strategy therefore depends on the right interpretation of complex data sets. Along with this, AI accelerates idea extraction cycles making an idea go from conception to completion in a shorter time. This swiftness is critical in a fast-paced market where dynamic responsiveness is considered a necessary condition. AI-assisted decisions in the R&D process brings relief to managers as it requires minimum resources and is automated. Through the identification of inadequacies and an improved way to plan, AI provides the necessary efficiency for companies to direct resources effectively. Achieving such a lean operation result in lowering costs and therefore the whole research and development operation finally turns out to be cheaper but more effective. Also, AI boosts human productivity through the automation of repetitive tasks, as well as analytical intel stickering. The collaboration of human intelligence and AI will always be critical to carrying on the ball of searching the novel paths and solutions that will eventually lead to innovative achievements. Besides, AI implementation fuels a tremendous raise in the quality and quantity of the inventions released. Companies will now start implementing AI - driven ease of decision making that will furnish them with untapped solutions and products. This will hence in return contribute to growth and competitiveness. However, such transformative prospects of AI are stipulated upon the adoption of agile leadership models and reorganization of the financial system (Karn, 2025). The leaders need to create an environment of constant development and gravitate towards AI's potential role in the evolution of novelty and the never-ending growth in order to compete in a cut-throat environment. The use of AI in R&D company and government management and in leadership poses a wide range of implications. These data highlight the transformative effect of AI on decision-making, innovation cycles, resource utilization, productivity, cost efficiency, and innovation outcomes. To enable the potential of AI, such an organization would need to develop a new style of (adaptive) leadership and reshape the organization to fit the evolving R&D management/leadership paradigm. Artificial intelligence (AI) is going to impact research and development (R&D) and innovation (innovation) in the near term, both of which are critical for growth and competitiveness.

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