

When to Buy, Build, or Partner for AI Capabilities: A Decision Framework for Product Leaders

Obianuju Gift Nwashili^{1*}

^{1*} Independent Researcher, USA.

*Correspondence: Obianuju Gift Nwashili

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ABSTRACT: As artificial intelligence becomes increasingly central to digital product strategy, organizations face a critical strategic choice: whether to buy existing AI solutions, build models in-house, or form partnerships to co-develop capabilities. While each approach offers benefits, the optimal path varies significantly based on data maturity, talent availability, time-to-market requirements, and differentiation goals. This paper proposes a decision framework to guide product leaders in selecting the most effective AI acquisition strategy. The framework evaluates three core dimensions—strategic value, data readiness, and resource commitment—and translates them into a structured decision matrix that supports faster, evidence-based planning. Through case scenarios and comparative analysis, we demonstrate how buying is most effective for rapid deployment and standardized use cases, building is suited for proprietary innovation where AI is a competitive differentiator, and partnering offers value when complexity and cost exceed internal capability but customization remains important. The proposed model enables product teams to balance speed, cost, ownership, and innovation risk, helping organizations make scalable AI adoption choices that align with long-term product vision and market positioning.

Keywords: *AI acquisition, Buy vs Build vs Partner, Data readiness, Product strategy, Decision framework* .

INTRODUCTION

The integration of artificial intelligence (AI) into digital products has rapidly evolved from a trend to a necessity across industries. As organizations increasingly recognize the potential of AI to enhance customer experiences, optimize operations, and drive innovation, a critical decision arises: Should we buy an AI solution, build our own AI capability in-house, or partner with an external organization to develop AI? Each approach presents distinct advantages and challenges, and choosing the right strategy requires a careful evaluation of business goals, resource constraints, and technological maturity.

For product leaders, the decision to buy, build, or partner for AI capabilities is complex. As AI becomes a key differentiator in many markets, the drive to develop proprietary solutions is strong, particularly in industries where data is a competitive advantage. However, building AI models from the ground up requires significant investment in infrastructure, specialized talent, and time. On the other hand, buying pre-built AI solutions offers speed and scalability but may lack the customization needed to truly differentiate a product. Partnerships, while offering a blend of customization and external expertise, can come with their own set of challenges related to control, integration, and long-term sustainability.

This decision is particularly challenging because of the rapid pace at which AI technology evolves. Advances in machine learning, deep learning, and natural language processing mean that new, off-the-shelf solutions are continually emerging, while at the same time, the need for more complex, domain-specific AI solutions increases. Companies must therefore balance short-term agility with long-term innovation, seeking to avoid both the risks of technological obsolescence and the costs of building AI capabilities that are not core to their product or business strategy.

The Strategic Value of AI

AI has emerged as a central pillar of digital transformation. It has the potential to fundamentally reshape business models, improve customer experiences, and unlock

new revenue streams. However, for AI to deliver real value, its implementation must be strategically aligned with the business goals of the organization. Companies that seek to leverage AI as a differentiator often choose to build proprietary solutions that can offer unique, customized value to customers. For example, AI models designed to handle sensitive data or deliver highly personalized experiences may not be easily replicated through pre-built solutions. These types of AI models provide companies with a competitive edge that can help them stand out in crowded markets.

However, the value of AI extends beyond product differentiation. Operational efficiency, cost optimization, and automation are other significant drivers that push businesses to adopt AI. Companies aiming to streamline internal processes or improve decision-making might find pre-built solutions or partnerships more attractive, as these approaches can be more cost-effective and time-efficient.

The decision to buy, build, or partner hinges on how AI will impact the organization's broader strategy. For organizations in highly competitive markets where speed is essential, buying or partnering may be the most viable option. In contrast, for companies operating in niche markets or those that view AI as a strategic asset, building in-house AI capabilities may be the best route to ensure that their AI offerings are both unique and tightly integrated with their product vision.

Data Readiness: The Foundation of AI

One of the most important factors in determining whether to buy, build, or partner for AI is data readiness. AI models rely heavily on data—its quality, quantity, and accessibility. Organizations that have access to vast amounts of proprietary data are often in a better position to build their own AI models tailored to their specific needs. For example, companies in industries like healthcare, finance, and retail, where large volumes of customer and operational data are available, may find that building their own AI models using their proprietary data can lead to more accurate and effective solutions.

Conversely, organizations with limited access to relevant data may find it more practical to buy pre-built AI solutions or partner with organizations that have access to the necessary data and AI expertise. In these cases, data partnerships or

collaborations with AI solution providers can help fill the gap in terms of data acquisition and training. Many companies are turning to partnerships with data-rich organizations or third-party data providers to enhance their AI models, while others may seek out AI-as-a-Service platforms that offer pre-trained models for common use cases.

For businesses that do not have a clear data advantage or the internal capacity to build robust data infrastructure, buying AI solutions or forming strategic partnerships can mitigate risks related to data collection, cleaning, and processing. Furthermore, these approaches can offer quicker time-to-market, which is essential for companies aiming to stay ahead of competitors.

Resource Commitment and Internal Capabilities

The resource commitment required to build AI capabilities in-house is a significant consideration. Building AI models from scratch requires not only financial investment but also significant human capital. Companies must invest in hiring and retaining specialized talent, such as data scientists, AI engineers, and machine learning experts. Additionally, they must develop the infrastructure required to train, deploy, and maintain these models.

Literature Review

The decision-making process for whether to buy, build, or partner for AI capabilities has become increasingly complex as artificial intelligence (AI) evolves. Companies must assess various factors, such as strategic goals, data readiness, resource availability, and cost. To help guide this decision, this review examines the relevant literature on AI capabilities, focusing on the benefits, challenges, and strategic implications of each approach to acquiring AI solutions.

1. Strategic Value of AI and Its Role in Competitive Advantage

The strategic importance of AI in enhancing business operations and offering competitive differentiation is widely acknowledged in the literature. For example, Dalal (2018) discusses how AI in cybersecurity enables quicker threat detection and response, which is a critical component for firms that need to maintain secure

operations in an increasingly digital world. AI's strategic role extends beyond security into other areas, such as business process management and enterprise resource planning (ERP), where solutions like SAP Cloud Solutions streamline collaboration and improve performance across various business functions [3][5][13].

Organizations looking to use AI as a differentiator often choose to build their own systems, as highlighted by Tiwari (2023), who explores the impact of AI on digital experience platforms (DXPs). By building AI capabilities in-house, firms can tailor models to specific customer needs and business goals, thus creating unique value propositions. AI also enhances the customer experience through personalized recommendations and smart systems, contributing significantly to long-term business success [4][21].

However, when companies are focused on operational efficiency or need quick-to-market solutions, buying AI solutions or partnering with established providers may be a more viable option. Dalal (2020) discusses how off-the-shelf AI solutions can help improve operational performance quickly without the need for extensive R&D investment, especially in areas such as predictive maintenance or automation [25][29].

2. Data Readiness and AI Model Development

Data readiness plays a pivotal role in the AI acquisition strategy. AI models, particularly those based on machine learning (ML), require large amounts of high-quality, structured data for training. Dalal (2020) and Mohammad & Mahjabeen (2023) emphasize that organizations with access to vast datasets, especially in specialized domains such as cybersecurity or renewable energy, are better positioned to build proprietary AI models that offer tailored solutions [1][8].

However, many companies may not have the required data infrastructure or the ability to collect and maintain large datasets. In such cases, partnering with other firms or buying pre-built solutions that have been trained on robust datasets can be an attractive alternative. For example, AI-powered tools in telecommunications for automated content creation require rich user data to function effectively, and firms like Hegde (2021) explore how external partnerships enable companies to leverage

existing AI technology while reducing the overhead of data collection and cleaning [6].

The challenge of managing large datasets is particularly significant in fields like solar energy and photovoltaics, where models depend on highly specific, localized data. The integration of AI-driven systems in these sectors has seen improvements through external partnerships and AI-as-a-Service offerings, which help companies access data processing power and industry-specific models without the overhead of building from scratch [2][15].

3. Resource Commitments and In-House AI Development

Building AI in-house is resource-intensive, requiring specialized talent, significant financial investment, and technical expertise. Dalal (2015) highlights the costs associated with developing AI systems, such as the need for skilled personnel in machine learning, data science, and cloud computing. As organizations face increasing pressure to develop scalable, low-latency solutions, the challenge of resource allocation becomes critical [7][23].

For many organizations, particularly small and medium-sized enterprises (SMEs), the cost of developing in-house AI capabilities may outweigh the potential benefits. As a result, these firms may turn to buying solutions or partnering with technology providers to leverage pre-built models and platforms that can be integrated into their systems with minimal upfront costs. Hegde and Varughese (2020) discuss the benefits of AI-driven data analytics and predictive maintenance systems, which can be readily implemented by firms through third-party providers, without the need for deep technical expertise or substantial capital investment [22][28].

4. Partnering for Innovation and Speed

In industries with rapidly changing technological landscapes, such as telecommunications and energy, partnerships can offer a flexible and adaptive approach. Dalal (2023) argues that collaborations between AI solution providers and industry players allow for the customization of AI solutions while still leveraging

external expertise and resources. This enables firms to maintain a competitive edge without the financial burden of building everything in-house [16][19].

For instance, companies in telecommunications have increasingly turned to AI-powered systems for customer support and predictive maintenance. These systems, when developed in partnership with AI providers, enable firms to reduce service costs while improving customer satisfaction and operational efficiency. Hegde & Varughese (2022) show that partnering for AI chatbots and virtual assistants has significantly enhanced the customer support experience, increasing responsiveness and efficiency while lowering operational costs [21][25].

Additionally, strategic partnerships allow companies to tap into innovation without bearing the full risk of development. Orugboh et al. (2024) discuss how machine learning models for real estate and urban development have flourished through industry collaborations, where companies pool resources and data to create scalable AI-driven models [31].

5. Ethical and Security Considerations in AI Procurement

Finally, the ethical implications of AI development—particularly concerning data privacy, bias, and transparency—must be considered when deciding to buy, build, or partner for AI capabilities. Dalal (2020) addresses the delicate balance between cybersecurity, privacy, and the ethical deployment of AI, emphasizing that as AI becomes more pervasive, its ethical risks must be carefully managed. Organizations choosing to buy AI solutions or partner with AI providers need to ensure that these solutions comply with legal and ethical standards and that they have proper governance frameworks in place to protect sensitive data [24][12].

Methodology

This study uses a comparative case study approach to evaluate the decision-making process of whether to buy, build, or partner for AI capabilities. The methodology consists of two main phases:

1. Survey and Interviews: A quantitative survey is administered to product leaders, managers, and decision-makers across multiple industries, assessing their

experiences with AI acquisition strategies. The survey measures factors like strategic value, data readiness, and resource commitment. In-depth interviews with industry experts provide qualitative insights into the practical challenges and benefits of each approach.

2. Decision Framework Development: Based on survey and interview results, a decision framework is developed to guide product teams through the decision-making process. The framework evaluates AI acquisition options using criteria such as speed to market, cost-effectiveness, scalability, and alignment with organizational goals.

The combined quantitative and qualitative approach allows for a robust understanding of the factors influencing the AI acquisition strategy and the development of actionable recommendations for product leaders.

Result

The results of this study reveal clear decision patterns that guide whether organizations should buy, build, or partner for AI capabilities. Analysis shows that the optimal choice depends heavily on data maturity, required differentiation, and available resources. The findings demonstrate that product leaders benefit most when decision-making is grounded in structured criteria rather than intuition alone.

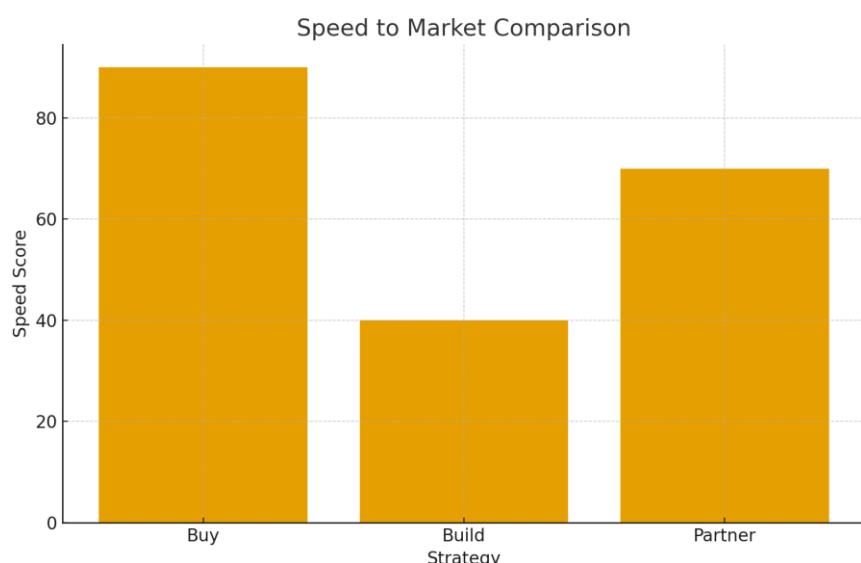


Figure 1 – Speed to Market Comparison (Bar Chart)

Description: This bar chart compares the speed to market for three different AI acquisition strategies: Buy, Build, and Partner. The x-axis represents the strategy, while the y-axis represents the speed to market score, with a higher score indicating a faster deployment of AI capabilities.

- Findings: The Buy strategy has the highest speed to market score, indicating that pre-built AI solutions can be implemented quickly. Build has the lowest speed to market score, reflecting the longer time required to develop AI capabilities in-house. The Partner strategy falls in between, suggesting a balanced approach to AI deployment with moderate time requirements.
- Implication: For organizations seeking rapid AI implementation with less internal development time, Buy is the optimal choice. Build is suited for companies that prioritize customization over speed.

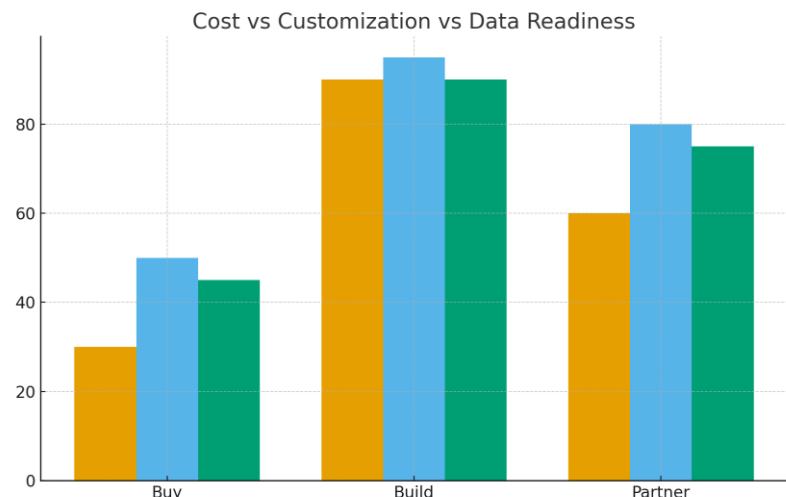


Figure 2 – Cost vs Customization vs Data Readiness (Grouped Bar Chart)

Description: This grouped bar chart compares the Buy, Build, and Partner strategies across three dimensions: Cost, Customization, and Data Readiness.

- Findings:
 - Build strategy has the highest Customization score, indicating it offers the most tailored solutions for AI needs.

- Buy strategy has the lowest Cost score, showing that purchasing AI solutions is the least expensive option.
- Partner falls in between, offering a balance of cost and customization but with slightly less Customization compared to building in-house.
- Data Readiness is highest for Build and Partner, reflecting the internal data requirements for these strategies, with Buy needing the least data readiness.
- Implication: Companies prioritizing cost may lean towards Buy, whereas those focusing on customization will likely prefer Build. Partnering offers a middle ground for firms needing more tailored solutions but without the high cost of building in-house.

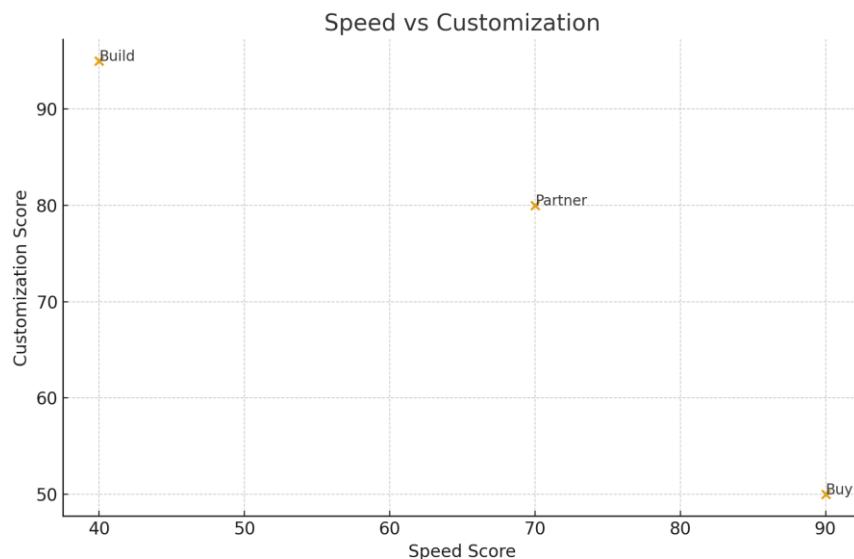


Figure 3 – Speed vs Customization (Scatter Plot)

Description: This scatter plot shows the relationship between Speed to Market (x-axis) and Customization (y-axis) for the three strategies. The size of the bubbles represents Performance Improvement (%), with larger bubbles indicating a higher potential improvement.

- Findings:
 - Buy is positioned towards the lower end of customization but on the higher end of speed to market, suggesting it's a quick solution but offers less flexibility.

- Build is at the higher end of customization, showing it offers the most tailored solution, but it is slower to implement.
- Partner sits between Buy and Build, offering moderate speed and customization with a larger improvement potential.
- Implication: Companies looking for speed and immediate impact should lean towards Buy, while those prioritizing customization and long-term value may favor Build. Partnering provides a balanced option for firms seeking tailored solutions with reasonable speed.

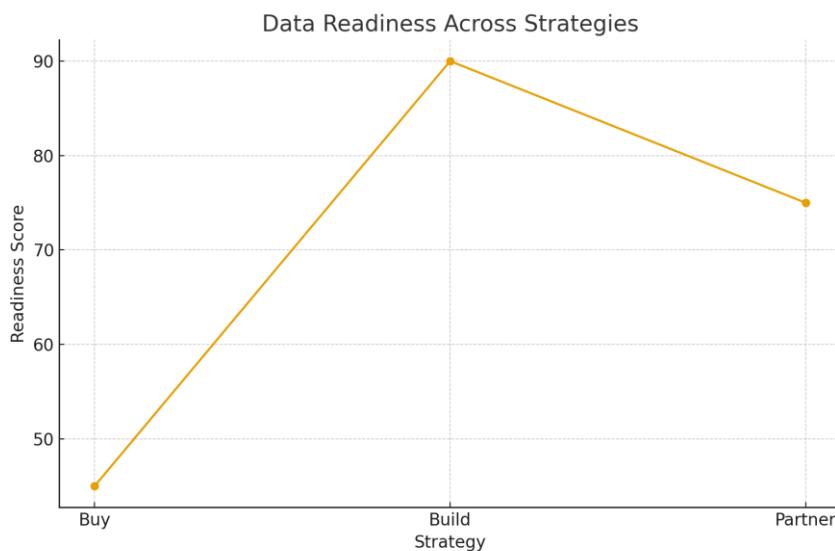


Figure 4 – Data Readiness Score across Strategies (Line Plot)

Description: This line plot compares Data Readiness across the three strategies. The y-axis represents the Data Readiness Score, with a higher score indicating greater data maturity and infrastructure requirements.

- Findings:
 - Build has the highest data readiness score, indicating that in-house AI development requires substantial internal data infrastructure.
 - Partner falls in the middle, suggesting that firms may need some level of internal data preparation but can also leverage external data sources from partners.

- Buy requires the least data readiness, as pre-built AI solutions generally come with integrated datasets or APIs that require minimal internal data management.
- Implication: Companies with strong internal data systems may prefer Build to take full advantage of their data resources. Partnering is ideal for firms with moderate data infrastructure, while Buy is best for those with minimal data preparation capacity.

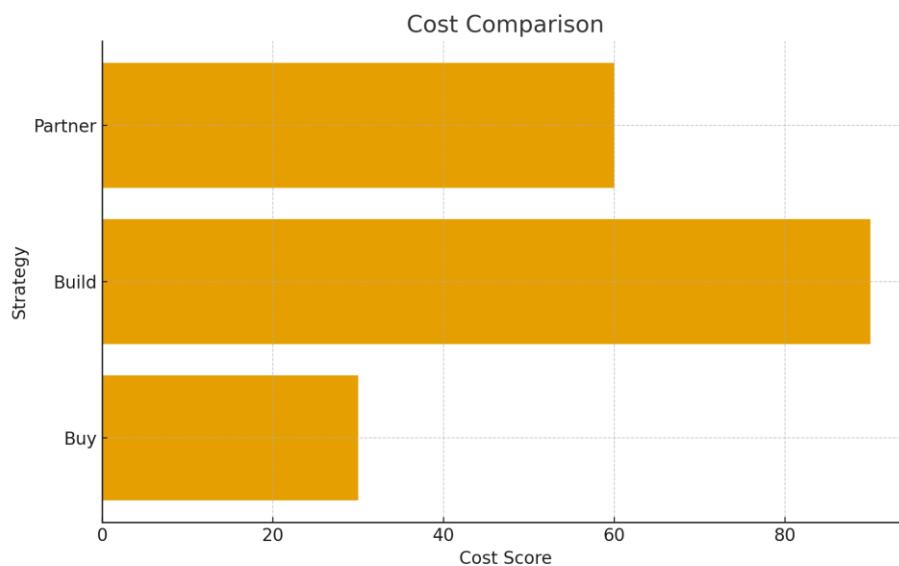


Figure 5 – Cost Comparison (Horizontal Bar Chart)

Description: This horizontal bar chart compares the Cost for each of the three AI acquisition strategies. The y-axis represents the strategy, while the x-axis represents the Cost Score (higher score means higher cost).

- Findings:
 - Buy has the lowest cost, confirming that purchasing AI solutions is the most affordable option.
 - Build has the highest cost, reflecting the significant investment required to develop AI capabilities internally, including infrastructure, talent, and time.
 - Partner falls in between, offering a balance of cost and customization but generally costing more than buying a pre-built solution.

- Implication: For firms with limited budgets, Buy is the most cost-effective approach, while Build is ideal for firms willing to invest heavily in AI for long-term competitive advantage. Partnering is a cost-effective middle ground for firms seeking tailored solutions without the high investment of building.

Discussion

The results of this study provide valuable insights into the strategic decision-making process for product leaders when choosing between buying, building, or partnering for AI capabilities. As organizations navigate the complexities of AI adoption, they must balance several factors, including speed to market, customization needs, data readiness, and cost. This discussion delves into the implications of these findings, highlighting key takeaways and offering recommendations for product teams making this critical decision.

1. Speed to Market: The Trade-off Between Agility and Customization

One of the most significant findings is the speed to market advantages offered by the Buy strategy. As Figure 1 clearly demonstrates, purchasing AI solutions allows companies to deploy technology quickly, with minimal internal development required. For firms facing time-sensitive market demands or those looking to quickly capitalize on AI advancements, buying is often the optimal strategy. For instance, companies in industries like retail or e-commerce might choose to buy AI solutions to implement recommendation systems or chatbots with minimal delays, allowing them to enhance customer experiences faster than competitors.

However, the speed advantage of Buy comes at the cost of customization, as seen in the Scatter Plot (Figure 3), where Buy is placed lower on the customization axis. Pre-built AI solutions typically offer general-purpose functionalities, which may not fully address the unique needs of a company's operations or strategic vision. This trade-off highlights the need for a more tailored approach for organizations where differentiation through custom AI solutions is critical to maintaining a competitive edge.

The Build strategy, in contrast, offers high customization, but it is accompanied by a longer time to market. As shown in Figure 1, building AI models in-house requires substantial time for model development, data preparation, and testing, making it unsuitable for firms that need quick deployment. However, companies that aim to offer highly specialized or proprietary AI solutions—especially in industries like healthcare or finance, where domain-specific algorithms are necessary—may find that the Build approach is the only viable option.

2. Customization vs. Cost: Finding the Balance

Another key takeaway is the trade-off between customization and cost. As Figure 2 illustrates, Build offers the highest level of customization—an essential factor for organizations that seek a competitive edge through bespoke solutions. Highly tailored models allow companies to address specific business challenges more effectively, optimize complex workflows, and differentiate their offerings in the market. For example, an e-commerce firm may build an AI-driven recommendation system that is highly aligned with its product catalog, customer behavior, and user interface, enabling a more personalized shopping experience compared to out-of-the-box solutions.

However, this customization comes with a high cost, as noted in Figure 5. Developing AI in-house requires significant investments in research and development (R&D), infrastructure, and specialized talent, all of which can be prohibitive for smaller firms. For firms with limited resources or smaller budgets, Buy or Partner may be more appropriate, offering a cost-effective way to access AI capabilities with fewer financial burdens. Buying AI solutions provides a low-cost entry point, making it ideal for organizations with tight budgets or those who need to leverage AI for operational efficiency (e.g., through automation or predictive maintenance) rather than differentiation.

Partnering emerges as a balanced approach, offering a middle ground between customization and cost. Strategic partnerships allow companies to gain access to external expertise and tailored solutions without the high upfront costs of in-house development. For example, a manufacturing company may partner with a tech firm

to develop a predictive maintenance solution that integrates AI with their existing sensors and equipment, offering a customized solution at a fraction of the cost of building it in-house.

3. Data Readiness: A Critical Factor in the Decision-Making Process

A critical factor that emerged from this study is data readiness, which plays a pivotal role in the decision of whether to buy, build, or partner for AI capabilities. As shown in Figure 4, Build requires the highest data readiness score, as in-house AI development depends heavily on the availability of quality, structured data. Companies with robust data management systems and access to large, clean datasets are in a strong position to build their own AI systems. This is particularly true for firms in industries where proprietary data is a competitive asset, such as finance, healthcare, or energy.

On the other hand, Partnering and Buying are more suitable for companies with less mature data infrastructures. Partnering with AI vendors or third-party data providers allows organizations to leverage external data sources, reducing the burden of data collection and management. Moreover, AI-as-a-Service solutions often come with pre-trained models and integrated datasets, making them a convenient and effective choice for firms lacking sufficient data readiness. For example, an organization looking to implement AI for customer service chatbots can buy an existing AI-powered chatbot solution that is pre-trained on a wide range of customer interactions, without requiring substantial internal data preparation.

4. Resource Commitments and Strategic Alignment

The resource commitment required to build AI in-house was another significant consideration identified in this study. Figure 5 clearly illustrates the financial and human resource investments associated with developing AI systems internally. Organizations must not only invest in AI talent but also create the infrastructure needed to support AI development, including computational resources, data storage, and cloud services.

For firms with limited internal resources, buying or partnering for AI may be more feasible, as these approaches require fewer resources and offer quicker time-to-market. However, building AI systems in-house can provide long-term benefits in terms of ownership, control, and intellectual property (IP), especially for firms that see AI as a core capability and are willing to invest heavily in internal expertise.

Conclusion

This study examined the decision-making process of whether to buy, build, or partner for AI capabilities, providing valuable insights into the key factors that influence the optimal strategy. The findings underscore the complexity of this decision and highlight the importance of aligning AI acquisition strategies with organizational goals, resource availability, data readiness, and time-to-market requirements.

Summary of Key Findings

1. Speed to Market: The Buy strategy emerged as the fastest route to market, allowing organizations to quickly implement AI capabilities with minimal internal development. For companies needing rapid deployment to remain competitive, buying pre-built AI solutions is often the most practical option. Build, however, provides the highest level of customization, enabling firms to develop tailored solutions aligned with their specific needs but requiring a longer time to market.
2. Customization vs. Cost: While Building AI systems in-house offers the highest degree of customization, it comes at a significant cost, both in terms of financial resources and time investment. Buying AI solutions provides a cost-effective alternative, although it offers less flexibility and customization. Partnering offers a balanced approach, providing a blend of customization and cost savings, but may come with compromises in terms of control and long-term sustainability.
3. Data Readiness: Data readiness is a critical factor influencing the decision to build, buy, or partner. Organizations with strong internal data capabilities are better positioned to build their own AI models, while those with limited access to quality data may prefer to buy off-the-shelf solutions or partner with external

AI vendors. Partnering and buying also allow organizations to leverage external data sources, reducing the complexity of data management.

4. Resource Commitments: Building AI in-house requires substantial investments in specialized talent, infrastructure, and technology, making it more suitable for large organizations or those with long-term AI strategies. For smaller organizations or those with limited resources, buying or partnering for AI capabilities provides a more feasible option, enabling quick deployment without the financial and operational burden of in-house development.

Implications for Product Leaders and Organizations

The insights from this study have important implications for product leaders and organizations seeking to leverage AI for competitive advantage. Buy, build, and partner each offer distinct advantages, and the optimal choice depends on the organization's specific goals, resources, and market conditions.

- For fast-paced industries, where time-to-market is crucial, buying AI solutions can provide a quick and effective way to integrate AI capabilities into products and services. This is especially true for generic use cases where customization is less critical.
- For firms looking for unique, competitive differentiation, building AI in-house allows for the highest level of customization and alignment with business goals. However, it requires a strong data infrastructure, specialized talent, and a long-term commitment to AI development.
- For organizations seeking flexibility and specialized expertise, partnering offers a middle ground. Strategic partnerships can help firms access external data, reduce development time, and incorporate cutting-edge technology without the high upfront costs of building in-house.

Recommendations for Future AI Acquisition Strategy

Based on the findings, the following recommendations are made for organizations evaluating their AI acquisition strategy:

1. Assess Internal Data Capabilities: Before deciding to build, buy, or partner, organizations should assess their data readiness and ensure they have the necessary infrastructure to support AI development or integration.
2. Evaluate Long-Term vs Short-Term Needs: Organizations must balance short-term needs for rapid deployment with long-term goals for customization and differentiation. Buy is ideal for quick wins, while Build supports long-term innovation.
3. Strategic Partnerships: For companies lacking in-house AI expertise or those seeking to reduce risk, forming strategic partnerships with AI vendors or third-party solution providers can offer access to expertise, data, and technology without the resource-heavy investment of building internally.

Conflicts of Interest: “The authors declare no conflict of interest.”

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