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Leverage Design Thinking to Build Enterprise AI

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Productionizing AI remains a challenge due to legacy technology and unequipped management.

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Introduction

Artificial Intelligence (AI) is hailed as a transformative technology of the 21st century, and Enterprise AI involves embedding AI into applications that support business processes.[1] Some typical examples of Enterprise AI are processing insurance brokers submissions for risk assessment, extracting information from shipping documents in logistics, and enhancing the due diligence process for investment decisions. Enterprise AI promises to bring efficiency, reduce costs, free employees from routine tasks and improve customer engagement. However, much of this promise remains unfulfilled. 90% of AI initiatives remain at proof-of-concept (POC) stage and do not make it to production.[2] This is especially true of well-established non-tech companies, where AI adoption is in its early stages and revenue streams are still based on traditional products and services. When compared to born-digital tech companies, these large non-tech companies have siloed structures and fragmented legacy business processes and systems.[3] Deploying AI into production remains an enduring challenge for these companies.

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Why is productionizing AI a challenge? Broadly, there are two major reasons: technology and management. Technology related reasons include difficulties in integrating with legacy enterprise systems, sustaining performance of AI models, developing machine learning operations (MLOps) pipeline for optimizing AI workflows and so on. Management related reasons include lack of experimentation mindset, top management support, expectations mismatch, unavailability of appropriate AI talent and so on. Though technology related reasons are being discussed by active involvement of the broader AI ecosystem and research community, management related reasons persist.[4] The complex structures of large non-tech companies necessitate a different style of management practices to make things work.[5]

A major impediment to translation of AI solutions from POCs to production is the contextual nature of such solutions. Solution developed for one use case in a particular domain cannot be directly reused for similar use cases in other domains. An AI solution developed to classify chest X-ray images for pneumonia cannot be directly reused to classify images of printed circuit boards for defects. An AI solution developed to retrieve information from retail invoices (business-to-consumer) cannot be directly reused to retrieve information from commercial invoices (business-to-business). An AI solution developed to analyze sentiments from software reviews cannot be directly reused to analyze sentiments from employer reviews. This context specificity if not appreciated during the POC stage may lead to stakeholders' expectations mismatch, which in turn leads to questions about the tangible benefits from the solution and lukewarm top management support. Translating POC to production requires that the division developing AI solutions considers the needs of their clients and end users throughout the process to bridge the gap between solution expectations and delivery and secures stakeholder buy-in at all stages of solution development. This raises the question as to how these large non-tech companies should involve various stakeholders (specifically, end users) collaboratively in the development of AI solutions and improve the production rates for their enterprise AI initiatives.

In this article, we propose a design thinking inspired framework to resolve some of the managerial issues with productionizing AI and specifically tackle the question of greater stakeholder involvement and support for the AI initiative. We also present two case studies of AI solution development in large non-tech enterprises as illustrations of how the framework may be applied to develop Enterprise AI solutions.

Design Thinking Inspired Framework

Design Thinking (DT) is a popular well-tested human-centered approach to integrate end users (potential customers) in the innovation process to develop products and services.[6] Design thinking has been utilized by large enterprises to great effect, albeit not in the AI space. For example, Ford Motor Company set up D-Ford labs globally (Detroit, London, Palo Alto, Melbourne, and Shanghai) to study customer experience and their needs deeply.[7] In these labs cross-functional and multidisciplinary teams brainstorm problem and solution spaces, develop prototypes, test & receive feedback from real customers, and iterate. One of their projects was the electric SUV Mustang Mach-E's entertainment system - Sync 4.[8] Another project was focused on F-150 truck where designers spent time immersing in the daily life of customers to deeply understand their needs.[9]

Design thinking confers tangible benefits to enterprises that utilize it in their processes. Studies done by the Design Management Institute and Motiv Strategies reported that companies who have institutionalized DT across the enterprise and who have tangible commitment from the senior leadership outperformed the Standard & Poor's (S&P) 500 Index by over 200% over 10 years.[10]

Adapting DT to the AI field involves taking advantage of diverse perspectives offered by various stakeholders in the company - AI, client (i.e., functional divisions), end users, business (typically people who sponsor or champion the initiative), Information Technology (IT) - and incorporating end users' explicit and implicit requirements while developing solutions. DT posits three spaces of innovation: inspiration, ideation, and implementation.[11] Inspiration is the motivating circumstance or business context that is searching for potential solutions. Ideation is the process of generating and experimenting ideas that could lead to potential solutions. Implementation is about charting a path from lab to market. Our framework builds on these three spaces and suggests a five step AI development process. The following Table 1 describes the five steps in our framework and maps them to the three spaces of innovation.

Table 1. Design Thinking inspired framework

Table 1. Design Thinking inspired framework.

Step	Description	Benefits	Design Thinking		
			Inspiration	Ideation	Implementation
1. Form a diverse team	Include people from diverse divisions – people from AI, client, business, IT, end users.	- Overcome constraints of professional and organizational silos - Avoid misunderstandings and information distortion - Every member brings their unique perspective that helps the other members see things they would not ordinarily see - Win commitments from multiple divisions to see through the AI initiative from idea to production	✓	✓	✓
2. Conduct needs discovery workshop	Understand client's business problem and generate many AI use cases; narrow down and sharply define AI use cases; observe what end users do in their work setting	- Shared understanding of the business problem - End users' perspective incorporated while developing AI use cases	✓		
3. Conduct hackathon	Build tangible prototypes using small purposive datasets	- Fail early and often - Identify strengths and weaknesses of the idea - Refine end users' needs - Articulate business value and get buy-in from business		✓	
4. Build POC	Create minimum viable solution using larger datasets; design application architecture and identify IT integration dependencies	- Build confidence to productionize the solution - Incorporate feedback from end users - Chalk out detailed plan - Articulate business value and get buy-in from business			✓
5. Productionize	Deploy AI solution; monitor performance and take corrective actions	- AI embedded within the enterprise IT system - End users adopt AI as part of normal business processes - Measure costs and benefits; reinforce business value			✓

Case Study 1: Fortune 100 Multinational Company

A multinational company is rapidly expanding into new geographies. Consistent on-time delivery of products for the company's customers builds their trust and loyalty and is an important driver of performance. The company seamlessly executes a series of operational activities to meet its package delivery commitments. One sub-activity within transportation is shipping products from one country to another. Several routine processes and documentation are executed by the associates using an in-house enterprise system to facilitate movement of products internationally. The company wants to use AI to bring efficiency in this sub-process.

The steps below explain how this project was conceptualized and executed.

Step 1: Form a diverse team

The core team comprised people from the following divisions:

- AI: data scientists and other specialists with complementary skills in AI technology and consulting
- Client: head of business function performing the transportation's sub-activity and other subject matter experts (SME)
- Business: country-level Vice President having a say in funding decisions and her direct reports
- IT: software architects and data engineers of the in-house enterprise system.

In a four-week exercise, leaders of the client and AI functions provided details of the overarching business process (i.e., international movement of products) in scope and clarified the as-is process. These discussions revealed the intensity of associates' manual data entry (product related information that is largely textual) into enterprise system. This led to the understanding that AI team would need expertise in natural language processing and associated techniques.

From a DT perspective, this is a foundational step, crucial for the inspirational space. Interactions among client, IT, and AI teams at the preliminary stage helped avoid misunderstandings and information distortions regarding in-scope process.

Step 2: Conduct needs discovery workshop

This step involved the core team travelling to the client's location where the business process was executed by associates. The client team presented their understanding of the business process, pain points, and where they anticipated an AI intervention. This was followed by active interactions among team members. Subsequently, the AI team presented their understanding of the business process and refined it based on feedback from other teams. Later, the AI team spent time directly observing associates (a few selected by the client) while they executed the routine processes and documentation. They also asked questions like: Could you explain how you processed a single product? Why did you do it this way? Is this being done for all products? What challenges do you face? and so on.

This step addressed the inspiration space. By deeply understanding the business process, end users' needs, and jointly articulating the use cases, the AI team narrowed down to a set of sharply defined use cases.

Step 3: Conduct hackathon

A three-day hackathon took place at the client location. AI, client, business, and IT teams assembled for this purpose, and chose small purposive datasets to execute the use-cases. There were frequent interactions between AI, client, and IT teams to understand what data would be useful. Once the data was obtained, AI team began experimenting and iterating with various models/algorithms. The focus at this stage was to develop executable but not production grade code. While in the beginning expectation from the client was to develop approaches with high accuracy levels, the AI team convinced the core team about the need to focus on robustness of the approach rather than accuracy. When the AI team assembled datasets, trained, and tested models, other teams (IT, client, business teams) also sat in the same room, with the AI team occasionally explaining their experiments and iterations. Finally, models were finalized for two use cases, and tangible prototypes developed. The prototypes involved explaining the dataset, approach used for building models, and model predictions. Despite getting accuracy in the range of ~60% for the use cases, active involvement and appropriate expectations convinced the business team about the approach and AI team received the go-ahead for POC and planning for productionizing.

This step illuminated the ideation space of DT by rapidly developing and testing potential approaches to solve the use cases in a manner that was visible to the core team and get their buy-in.

Step 4: Build POC

During this step, the prototypes developed during hackathon stage were enhanced with larger datasets for each use case. There was intense interaction between client and AI teams to understand and discover patterns in data through exploratory analysis. The AI team learnt that this is the stage for developing modular functions, code refactoring, removing workarounds, creating code documentation, etc. to adapt models to larger datasets and plan for integration with potential points in the enterprise system. At this stage experimentation and iterations were still not complete. Larger datasets had different patterns and the modeling approaches need to be tweaked. The AI team along with the client needed to think about what was needed to put this into production. Further, the team identified integration dependencies with the enterprise system through constant discussions with the IT team. The existing enterprise system was not configured to provide feedback (to learn the actual inputs given by associates) to an AI model. The IT team made appropriate modifications to the enterprise system to facilitate providing this feedback. The enterprise system was designed in a such way that the response from any external service had to be less than ~300 milliseconds. To ensure this response time, code optimization (for example, parallel processing) was done without compromising the accuracy. Interestingly, the client added a few more use cases (identified during the needs discovery workshop but not included for hackathon) to the overall AI project, and a separate team developed POCs for these processes.

This step illuminated ideation and implementation spaces of DT, by furthering iterative development and testing, and charting the path for a production ready solution.

Step 5: Productionize

In this step, the AI models were embedded within the company's in-house enterprise system. During the transition stage from POC to production, the team realized that deep learning would be able to provide better performance than the ML models. This required special approvals not sought earlier. Significant improvements in performance convinced the information security team to reconsider their legacy approval process and specialized deep learning packages were given approval after several discussions with AI, client, and IT teams. Deploying models on production also involved thorough code vulnerability assessments and frequent interactions between IT and AI teams to resolve issues. Processes are also put in place for a feedback loop where incorrect predictions are noted, and the learning is fed back to the model during retraining. Models are retrained every month with new data by the AI team.

From a DT perspective, this step illuminated the implementation space. The core team experienced the complete cycle (from step 1 to step 5) and was involved throughout.

Forming a core team from diverse divisions is a crucial step that has implications across DT spaces. This core team was able to win commitments from multiple divisions to see through the AI initiative from idea to production.

Case Study 2: Government Agency

A government agency that functions to ensure public safety receives information (word of mouth, intercept, anonymous letter, etc.) from various sources. The current process of analyzing this information is manual. Information received is noted as free form text. An AI system needs to analyze this unstructured textual information to flag important information that indicates a public safety risk. Additionally, the system should explain why the information was flagged. The end user should be able to comprehend this explanation and decide on the course of action.

Step 1: Form a diverse team

The core team comprised of people from the following divisions:

- AI: data scientists and other specialists.
- Client: Chief Data Officer of the agency and other SMEs with multiple years of experience
- Business: Chief Data Officer and Data Policy Advisor from the government who have a say in funding decisions
- End users: frontline employees, analysts, managers
- DT: design thinking experts with multiple years of experience.

Leaders of client and business divisions identified the scope for AI engagement as analyze unstructured information and flag important information along with the reasons for flagging.

Step 2: Conduct needs discovery workshop

Covid-19 related constraints necessitated a virtual design thinking workshop. AI and DT teams interviewed SMEs and potential end users of the AI solution to understand the information gathering and analysis process. All these interviews were unstructured with open-ended questions that allowed SMEs and end users to voice their ways of thinking about the process.

These interviews led to a fine-grained understanding of the information gathering and analysis process. Fundamentally, the process is executed by three groups of employees as follows:

- **Frontline employees:** They work in the “field” and gathers/documents the information (primarily textual data) from various sources like informants, members of public, etc.
- **Analysts:** They are skilled in data analysis and identification of patterns. Analysts sift through the information shared by frontline employees and refer to the information present in government databases, geographical information systems, etc. to

corroborate or collect further information. Analysts then perform link analysis (mapping relationship between entities), event charting (depicting sequence of related events over time), and flow analysis (depicting the flow of artefacts among entities.) and generate flags.

- **Managers:** The information flags generated by analysts are used by managers to make resource allocation decisions based on contextual knowledge. The AI solution must provide easy-to-understand explanation (i.e., why the information was flagged) to managers for them to trust the AI solution and have confidence in their resource allocations.

From a DT perspective, these two steps involve the inspiration space

Step 3: Conduct hackathon

A one-week hackathon was conducted. Unlike the first case, the focus here was not to build AI models on small datasets but rather simple prototypes of the solution i.e., what AI models would be potentially needed for the solution. The prototypes developed during hackathon provided a foundation for POC and model building. Though the subsequent steps (i.e., provide POC and productionize) of this initiative are ongoing, the first three steps demonstrated the value of DT approach to conceptualize an AI solution.

Conclusion

Building and implementing value accretive Enterprise AI in large companies is a complex activity. Design thinking can be helpful in these contexts by involving the end users and subject matter experts early in the process. This framework helps to identify the most impactful areas for AI intervention by capturing the needs of end users. This is achieved by tapping into the knowledge of a diverse team, conducting iterative needs discovery workshop, shortlisting the most impactful use cases, conducting hackathon for prototype development, building a proof-of-concept, and finally productionizing the system. Business leaders should not impose this framework on the entire AI division and all its projects in one go. Rather, this framework must be first used for envisioning a few AI projects. This will allow the core team to experience the full cycle and use the learnings gained to refine the framework based on the unique culture and context of the company for future projects.

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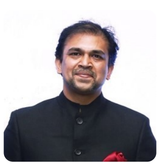

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