daBML - an extension on the "Build Measure Learn" loop for generative AI process adoption

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Abstract. Startups adopting generative AI (GenAI) often face challenges not addressed by existing enterprise-oriented frameworks. Fast feedback cycles, resource constraints, and high uncertainty require a lightweight approach that goes beyond traditional maturity models. This chapter introduces *Define-Analyse-Build-Measure-Learn* (daBML), an extension of the Build-Measure-Learn (BML) loop, tailored to guide generative AI adoption in startup environments. By adding two upstream phases — *Define* and *Analyse* — the framework supports clearer scoping, risk awareness, and value alignment before experimentation begins. The framework is illustrated through two internal use cases from a later-stage software startup, covering domains such as software development, product design, operations, and commercial outreach. These examples demonstrate how daBML can help teams frame GenAI initiatives, identify adoption risks, and track impact through lightweight iterations. While promising in practice, the framework remains conceptual and is not yet empirically validated. Future work should explore how daBML performs across varied startup contexts and how it supports long-term integration of generative AI beyond initial pilots.

Keywords: Generative AI · Toolset · Build-Measure-Learn · Technology Adoption · Organisational Impact.

1 Introduction

As generative AI (GenAI) capabilities continue to develop, organisations are actively exploring how these systems can function as internal assistants to streamline workflows and enhance operational efficiency [9, 41]. For startups in particular—especially those operating in software development—generative AI is increasingly viewed as a tool to support automation, boost creativity, and accelerate decision-making cycles [20, 44]. Studies have documented generative AI applications across departments such as Marketing, IT, Operations, Risk, and Human Resources, showcasing its potential to reshape work practices and augment human capabilities [8, 15].

Despite this growing momentum, it remains unclear how startups can effectively adopt generative AI technologies [6, 43]. Several questions remain open:

which departments and roles benefit most from generative AI? How do these tools restructure workflows or responsibilities? And what strategies can guide adoption under constraints of limited resources, technical expertise, and time [6, 44]? Compounding this uncertainty is the difficulty of determining the right timing and scale of investment to ensure measurable returns [13, 22].

In response, a growing body of research has begun to address the organisational and strategic dimensions of AI adoption. Prior work has proposed AI capability assessment models, AI maturity frameworks, and phased adoption strategies aimed at supporting structured integration [4, 7, 21, 27]. However, these models are largely tailored to enterprises and may not sufficiently reflect the dynamic, iterative, and resource-constrained realities of startup environments [2, 38]. While some studies explore the financial valuation of AI-driven businesses [34], others highlight the importance of aligning AI initiatives with business goals through structured evaluation frameworks [11, 23].

For software startups generative AI offers opportunities for rapid prototyping, workflow automation, and cost reduction—particularly in areas like product development, recruitment, software testing, and customer engagement [44]. However, implementation is not without challenges. Startups often face high setup costs, limited generative AI literacy, and uncertainty in estimating long-term impact or return on investment [25, 36]. Moreover, issues related to intellectual property, model bias, and compliance further complicate adoption, especially in the absence of dedicated AI governance structures [29, 50].

Against this backdrop, it becomes evident that startups require more than generic AI maturity models or enterprise-oriented toolkits. What is needed is a lightweight, flexible approach that accommodates fast-paced experimentation while maintaining strategic clarity and risk awareness. Such an approach should help startups not only to identify relevant generative AI opportunities, but also to reflect critically on feasibility, organisational readiness, and long-term value. This chapter addresses that need by exploring how structured yet adaptive frameworks can support generative AI adoption in startup environments. Building on startup-centric methodologies and informed by recent research, it introduces a process model designed to support intentional, iterative, and low-risk adoption of generative AI within software startups.

2 State of the art

2.1 Generative AI in the business

Generative AI has demonstrated significant potential across several key impact areas within startup environments, particularly those characterized by resource constraints and high levels of uncertainty. The most frequently cited domains include productivity, creativity, decision-making, automation, innovation, and knowledge management. These areas represent the primary vectors along which generative AI can drive tangible improvements in business performance.

In terms of productivity and automation, generative AI enables startups to reduce manual workloads by automating repetitive and time-consuming tasks

[50]. This includes areas such as internal documentation, customer service automation, and content summarization, allowing employees to focus on higher-value work [8, 17, 31]. These capabilities directly contribute to increased operational efficiency and lower process overheads. Creativity and innovation are equally prominent themes in generative AI literature. Tools like large language models and image generators can augment human ideation and content production, acting as co-creators in marketing, product design, and software development workflows [8,31,45]. This augmentation accelerates early-stage experimentation and supports broader innovation cycles, especially relevant in startups seeking novel business models or rapid prototyping capabilities [30, 37].

In the context of decision-making generative AI tools offer domain-specific assistance by extracting insights from large volumes of data, providing recommendations, and generating synthetic outputs that inform strategic choices [16, 26, 33]. This includes applications across engineering, HR, and operations where fast, informed decisions are critical [17, 30, 42]. Such support can enhance decision quality, reduce biases, and speed up analysis in high-stakes or time-sensitive scenarios.

Knowledge management is another area where generative AI can add value, particularly by generating onboarding documents, FAQs, meeting summaries, and contextualized internal communication [31, 42]. These applications facilitate organizational learning and internal transparency, helping startups maintain alignment as they scale.

Finally, the measurement of generative AI impact has increasingly moved beyond traditional financial metrics. Recent frameworks emphasize the importance of tracking KPIs such as efficiency gains, user adoption rates, time saved per task, and employee satisfaction to assess the real-world value of generative AI deployments [24, 32, 45]. These indicators support data-driven iteration and help align generative AI initiatives with strategic business goals.

2.2 Existing Adoption Frameworks and Limitations

Organisations adopting new technologies have long relied on established frameworks such as the Technology Acceptance Model (TAM) [12, 48], the Technology–Organisation–Environment (TOE) framework [3,46], Business Process Management (BPM) [14], and DMAIC from Lean Six Sigma [1]. While each contributes valuable perspectives—user intentions (TAM), organisational context (TOE), structured process improvement (DMAIC), and workflow optimisation (BPM)—they share significant limitations when applied to startups experimenting with generative AI. These models are largely enterprise-oriented, assume stable environments, and lack the agility needed for early-stage experimentation [28, 51].

Other frameworks, such as McKinsey's 7S [40, 49] and ADKAR [19], focus more on internal alignment or individual-level change management, offering limited value for organisations undergoing fast-paced technological transformation. Even the Build-Measure-Learn (BML) loop [39], widely embraced in startup product development, falls short when applied to complex internal adoption efforts—it prioritises speed over analytical depth and often lacks structured guidance for risk or stakeholder alignment [10].

In contrast, a growing body of literature directly addresses the challenges of generative AI adoption. The AI Capability Assessment Model (AI-CAM) by Butler et al. [7] evaluates maturity across business, ethics, data, and governance domains. Holmström and Carroll [20] offer a strategic typology of AI innovation strategies along augmentation and automation axes, while Strobel et al. [42] introduce a taxonomy of GenAI system types and associated risks. These models are helpful in classifying innovation types and surfacing early risks, but offer little in the way of a repeatable process.

Gupta et al. [18] contribute a startup-specific adoption model for prototyping technologies, incorporating factors like recyclability, ease of use, and behavioural intention. Although not exclusive to AI, it is particularly relevant for early-stage GenAI experimentation. Bettoni et al. [4] focus on SME readiness, highlighting constraints such as limited data, low technical literacy, and cost. Baek et al. [2] propose a quality evaluation model for AI-based services, grounded in user experience and feedback loops—highly aligned with startup needs. Tursunbayeva and Gan [47] contribute a holistic checklist (TOP framework), emphasizing organisational culture, trust, and workforce empowerment.

While these frameworks provide valuable insights—particularly around readiness, risks, and classifications—most remain descriptive and fragmented. Few offer a lightweight, actionable process tailored to the realities of startups: limited resourcing, fast iteration cycles, and uncertain returns. The daBML framework addresses this gap by integrating strategic scoping, feasibility reflection, and lean experimentation into a repeatable adoption process—bridging the divide between academic models and startup practice.

3 Research method

In this paper, we present a conceptual framework aimed at guiding the adoption of generative AI in later-stage startups. The approach is exploratory and design-oriented, with a strong emphasis on practical relevance and applicability.

First, the *daBML* framework was constructed as a conceptual extension of the Build-Measure-Learn loop. While not the result of a formal empirical study, the framework draws conceptually on academic literature discussing the limitations of existing adoption models and the emerging characteristics of generative AI technologies. Rather than aiming to develop a new theory, the framework seeks to offer a practitioner-oriented structure that responds to recognised gaps in current practice—particularly regarding risk awareness and strategic alignment prior to experimentation.

Secondly, the framework is illustrated through a real-world use case involving a later-stage startup. Four real examples—based on actual organisational decisions and adoption scenarios—are used to demonstrate how the framework could be applied in practice. These examples help to ground the framework in realistic startup dynamics and validate its relevance across different types of generative AI integration.

By combining conceptual development with practitioner-oriented explanation and grounded illustration, this study contributes a toolset that supports structured yet agile adoption of generative AI technologies in startup environments.

4 Key findings

4.1 Build-Measure-Learn as the foundation for (AI) adoption in startups

The Build-Measure-Learn (BML) loop, introduced by Ries in the Lean Startup methodology [39], has emerged as a widely adopted model for structuring innovation and experimentation in startup environments. Although originally developed for product validation, BML's underlying principles—rapid iteration, minimal upfront investment, and real-world feedback—make it well-suited to internal innovation contexts as well.

For example, Cook [10] applies BML to educational innovation, showing how it can be used to introduce and iterate on internal processes by treating users (e.g., students or staff) as key feedback sources. This reinforces the idea that process adoption can mirror product adoption: both involve building something new, rolling it out to users, and refining based on real-world interaction and adoption behavior. In this way, BML's learning cycle becomes a practical tool for testing not only external products but also internal technology-driven changes such as generative AI use cases.

Both require rapid feedback, fast iteration, and a minimal investment approach to reduce uncertainty and validate value creation. Its core premise—rapidly building a minimal viable implementation (MVI), measuring outcomes, and iteratively learning from real-world feedback—aligns well with the fast-paced and resource-constrained reality of startups. For later-stage startups (10–50 employees), the BML approach continues to offer a pragmatic structure to navigate uncertainty, particularly when experimenting with emerging technologies like generative AI [5, 45].

Compared to more established process and technology adoption models—such as TAM, TOE, BPM, or DMAIC discussed in Section 2—BML offers significantly greater agility and responsiveness. Traditional models tend to emphasize structured planning, user acceptance, or enterprise-wide alignment, making them less suitable for fast-paced experimentation in uncertain startup environments. In contrast, BML provides a lightweight, learning-oriented cycle that prioritizes user input and rapid iteration over rigid planning or top-down implementation [35].

However, as discussed in Section 2, BML also has notable limitations when applied to the adoption of complex technologies like generative AI. It lacks structured mechanisms for framing innovation goals, assessing feasibility, or anticipating organisational risks—factors that are especially important given the broader scope, uncertainty, and potential impact of generative AI initiatives. Such technologies frequently intersect with ethical concerns, regulatory ambiguity, data governance, and workforce dynamics. In short, misaligned or premature adoption can lead to wasted resources, trust erosion, and unintended consequences at scale.

To address these challenges, we position BML not as a standalone solution but as a foundational component to be extended. The *daBML* framework builds on the strengths of BML while introducing two preceding phases: *Define* and *Analyse*. These additions provide startups with tools for clearer scoping, early risk reflection, and strategic alignment—before entering the experimental Build-Measure-Learn cycle. In the following sections, we present the complete framework and illustrate how these components enhance the applicability of BML in generative AI adoption contexts.

4.2 daBML

The growing interest in adopting generative AI within startups is met with a fragmented body of frameworks, most of which either lack the iterative speed needed for early-stage ventures or fail to provide practical guidance on how to assess and measure impact. While existing process models such as the Build-Measure-Learn (BML) loop from the Lean Startup methodology offer a strong foundation for rapid iteration, they fall short in analytical depth—particularly when applied to AI adoption contexts that require risk evaluation, capability assessment, and impact measurement. To address this gap, we introduce the daBML framework: an extension on the Build-Measure-Learn loop (figure 1). The framework consists of the BML logic but expands it with two preceding phases - *Define* and *Analyse*, — each grounded in insights from recent literature on AI capabilities, typologies, and governance models. As presented in the framework, we see that phases: *Build*, *Measure*, and *Learn* represent the 3 phases of the BML cycle. If needed to be classified under one of the BML components the *Define* and *Analyse* phases would align best with the concept of learning and are hence grouped under *Learn*. When trying to align the core of the BML extension with a fitting title, we constructed *daBML*. Since the abbreviation BML is widely used for the Build-Measure-Learn loop, and this toolset is merely an extension on the framework, we add 'da' to represent the new components *Define* and *Analyse* respectively.

1. Define This phase marks the starting point of the framework. Startups clarify what they aim to achieve, assess their current capabilities, define which type of innovation aligns with their strategic direction, and select the type of generative AI technology. Based on this, they select key impact areas and formulate KPIs that will later guide implementation and evaluation. The KPIs established here serve as the baseline for the *Measure* phase. In addition, the chosen strategic direction and AI type help set the scope and reveal early limitations to be explored in the *Analyse* phase.

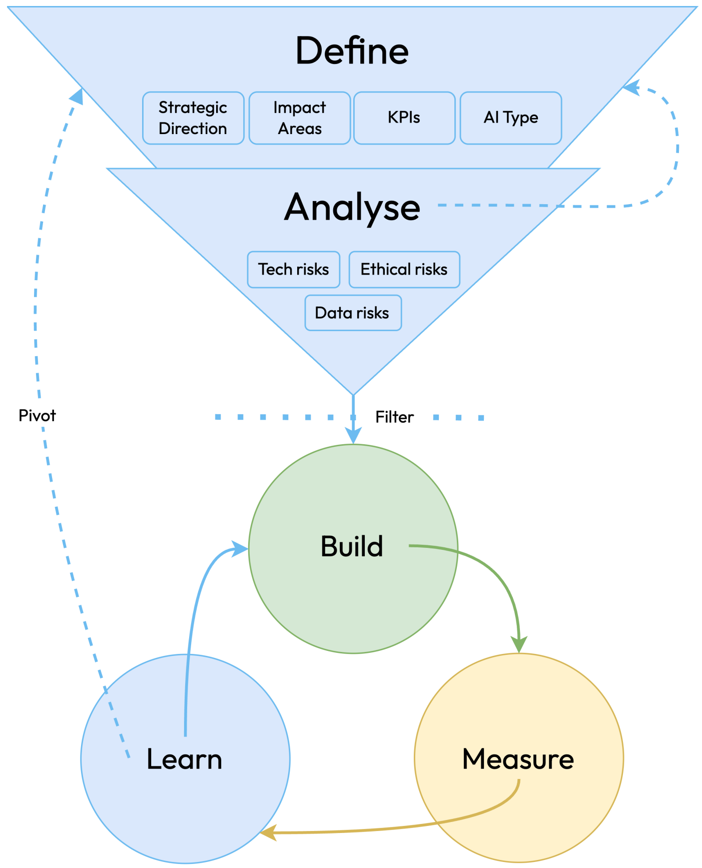

Fig. 1: Visual representation of the daBML framework. The process starts with two upstream phases — *Define* and *Analyse* — that guide strategic direction and assess risks before entering the iterative Build-Measure-Learn loop.

2. Analyse This phase serves as a lightweight filter before committing to experimentation. Startups quickly assess potential risks and limitations related to the proposed use of generative AI. This includes technical risks (e.g., integration complexity or system downtime), data-related concerns (e.g., GDPR, privacy, and security), and ethical considerations (e.g., bias, transparency, and trust). The goal is to surface potential blockers early—without overengineering the process—so that informed decisions can be made on whether to proceed or adapt. This risk-aware reflection builds on the strategic direction and AI type from the previous phase. The insights here help shape the boundaries and focus of the *Build* phase.

3. Build With a clearer direction and risk awareness in place, startups move on to developing a Minimum Viable Implementation (MVI). The MVI tests the value of generative AI in a focused area of the business. To keep the process lean, startups often use off-the-shelf tools and involve end-users early to gather feedback. The MVI is informed by the priorities and constraints identified in the previous phases. It's intentionally scoped using the KPIs and risk filters already defined.

4. Measure This phase focuses on evaluating the performance of the MVI using the KPIs defined earlier. Beyond just tracking metrics like efficiency or accuracy, startups also collect qualitative feedback to capture usability and perceived value. The combination of KPI tracking and user feedback provides evidence on whether the strategic goals from *Define* are being met in practice.

5. Learn Startups synthesize findings from both quantitative and qualitative results to determine next steps. They may choose to scale up, refine and iterate, or pivot to a new approach—depending on what they've learned. Evaluation outcomes loop back into earlier phases: feeding into a new *Define* phase (in case of a pivot) or directly informing the next *Build* phase (in case of refinement).

4.3 The 'new' components, what is da?

Define: context and framing The first component of the daBML framework — *Define* — serves as the foundation for any generative AI adoption effort. Its primary aim is to establish strategic clarity before engaging in technical experimentation or implementation. In this phase, startups articulate the intended purpose of the AI initiative, the organisational context in which it will be deployed, and the expected business outcomes. This includes identifying which roles, departments, or processes will be affected, and clarifying the overarching goals such as improving productivity, augmenting creativity, supporting decision-making, or streamlining operations.

A core part of this step involves examining several contextual considerations: Which internal stakeholders or teams will be most impacted by the initiative? What organisational pain points or inefficiencies are currently present in the targeted process? What would success look like from both a business and end-user perspective? How will the added value of generative AI be recognised or demonstrated early, even before formal KPIs are established? And finally, what assumptions are being made—explicitly or implicitly—about the potential of generative AI in this specific context?

By setting the context early on, startups can avoid the pitfalls of vague or overly ambitious AI projects that lack strategic alignment. This framing phase is particularly crucial in resource-constrained environments, where experimentation without clear direction can lead to wasted effort or misalignment with core business needs.

Define: applying theoretical models To further ground the strategic direction, the *Define* phase incorporates conceptual models that help teams frame

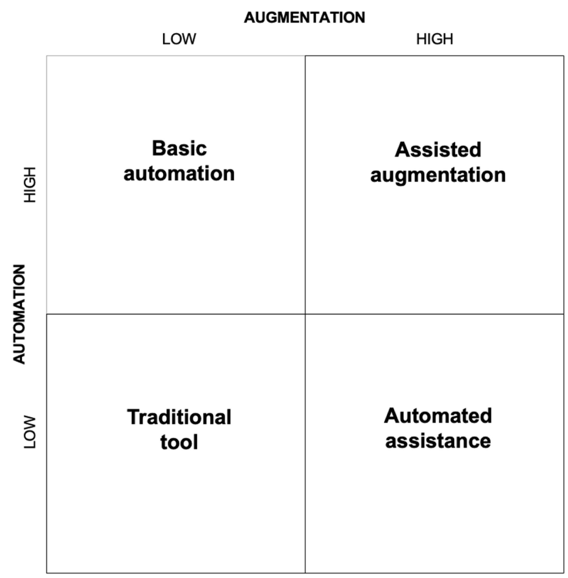

Fig. 2: Quadrilateral model of Holmstrom and Carroll [20] © 2024, used under CC BY 4.0 license.

their generative AI use case. One such model is the quadrilateral framework proposed by Holmström and Carroll [20], which distinguishes AI innovation strategies along two dimensions: the degree of automation and the extent of augmentation of human capabilities. This model enables startups to classify potential use cases into four quadrants, helping to surface underlying assumptions about the role of AI in the target process. As shown in Figure 2, the quadrants include: *(i)* low automation and low augmentation, where minimal AI involvement may indicate that traditional tools suffice; *(ii)* high automation and low augmentation, typically aligned with rule-based or repetitive task automation; *(iii)* low automation and high augmentation, which supports human expertise and creative output; and *(iv)* high automation and high augmentation, where AI actively contributes to decision-making or co-creation. By situating a proposed use case within this space, teams gain a clearer sense of scope, required capabilities, and the anticipated interaction between human and AI actors. This classification also initiates a critical line of questioning: Are we seeking efficiency through automation, enhancement through augmentation, or both? What level of human involvement is expected or desired? These early reflections are essential for shaping the evaluation criteria and feasibility assessments that follow in the next phase.

Following the strategic classification of objectives using the automation - augmentation space, the next step involves selecting the appropriate type of generative AI technology to support the intended business value. To this end, the typology proposed by Strobel et al. [42] offers a structured lens through which

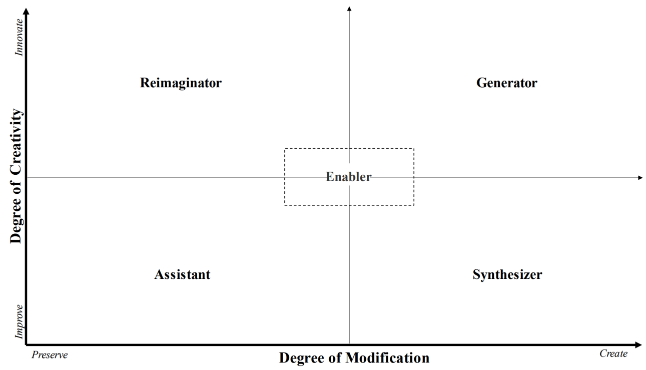

Fig. 3: Typology matrix of Strobel et al. [42] © 2024, used under CC BY-NC-ND 4.0 license.

startups can categorize potential generative AI applications. This mapping helps translate abstract strategic aims into concrete AI functionalities, ensuring that selected tools align with the specific nature of the intended outcomes.

Strobel et al.'s framework identifies five distinct categories of generative AI systems, each suited to different types of value creation. *Generators* are designed for novel content creation and are particularly relevant in contexts like marketing, communications, or product design, where original output such as text, imagery, or video is required. *Reimaginators* focus on transforming existing material while retaining its core intent—making them suitable for tasks such as editing, personalization, or format adaptation, often used in internal knowledge sharing or communication workflows. *Assistants* provide targeted, domain-specific support and are often deployed in environments such as engineering, legal, or customer service, where contextual understanding and operational relevance are key. *Synthesizers* are effective in generating summaries or synthetic outputs from complex data, serving use cases that demand data aggregation, reporting, or insight extraction. Finally, *Enablers* constitute the infrastructural layer of generative AI, offering capabilities for scalable deployment, integration with enterprise systems, or support for other AI services.

The process of aligning generative AI typologies with business objectives involves reflecting on the type of value the organisation seeks to deliver—whether that be innovation, optimization, or enhanced support capabilities—and assessing which generative AI type is most likely to realize those outcomes. This typological mapping complements the earlier strategic framing and helps refine the technical scope of the initiative.

Analyse The second phase of the daBML framework, *Analyse*, serves as a conceptual filter that helps assess the viability of the proposed generative AI initiative before committing to implementation. This phase builds upon the strategic framing established in the *Define* phase—particularly the innovation strategy derived from the automation–augmentation space and, where applicable, the selected generative AI typology. Its primary objective is to uncover key risks, constraints, and limitations that may otherwise go unnoticed in the rush to experiment.

By examining potential barriers related to legal compliance, data governance, ethical implications, and technical feasibility, startups gain a more complete understanding of the context in which the generative AI solution will operate. For instance, a solution classified as high automation and high augmentation—particularly when coupled with a *Generator*-type model—tends to carry elevated risk. These systems often produce novel outputs with limited human oversight, raising concerns around reliability, accountability, and safety. In such cases, additional controls or safeguards may be required before proceeding to development.

Key considerations at this phase include legal and regulatory compliance (e.g., data privacy, intellectual property, or sector-specific laws), as well as safety, interpretability, and accessibility. Startups should also reflect on feasibility—whether the necessary data, infrastructure, or expertise are realistically within reach—and whether the intended solution will be equitably accessible to its intended users. These reflective questions not only help to mitigate risk but also support responsible innovation by ensuring that the system's potential impact is assessed across operational, ethical, and social dimensions.

Ultimately, the *Analyse* phase helps determine whether to proceed with the proposed generative AI initiative as scoped, to revise certain assumptions or parameters, or to postpone implementation until foundational issues are addressed. It provides a lightweight yet structured opportunity to course-correct before resources are invested in building a Minimum Viable Implementation.

Table 1: Risk profiles based on innovation strategy (Holmström and Carroll [20])

Quadrant	**Risk Profile**	**Typical Risk Types**
L Aut / L Aug	Minimal innovation risk; potentially low value	Missed opportunity, underutilization of AI capabilities, user disengagement
H Aut / L Aug	High operational risk; low human oversight	Error propagation, system failure, over-automation, compliance issues
L Aut / H Aug	Human-AI interaction risks	Misguidance, trust erosion, cognitive bias reinforcement
H Aut / H Aug	Highest complexity and compound risk	Hallucinations, lack of traceability, ethical or legal violations, accountability gaps

4.4 Applying the Framework: Use Cases

To illustrate how daBML supports generative AI adoption in startup environments, we highlight two internal use cases from a late-stage European software startup (±50 employees). These examples demonstrate how the framework

Table 2: Risk profiles by generative AI application type (Strobel et al. [42])

generative AI Type	Risk Types	Notes
Generator	Hallucination, copyright/IP violation, bias, misinformation	Produces novel content; low control and verification of outputs
Reimaginator	Content distortion, confusion, trust issues	Alters existing materials; risk of altering meaning or tone
Assistant	Misleading advice, automation bias, over-reliance	Guides decision-making in domain-specific tasks; critical in regulated fields
Synthesizer	Data misrepresentation, nuance loss, bias amplification	Aggregates and condenses data; may obscure detail or introduce bias
Enabler	Integration complexity, infrastructure lock-in, data exposure	Underlying infrastructure risks; often hidden early in adoption

guides adoption through strategic framing, risk reflection, rapid experimentation, and iterative learning.

Use Case 1: AI-Assisted Code Generation (Technical) Context. Developers frequently encountered repetitive coding tasks in both legacy and greenfield environments. These low-value tasks contributed to cognitive fatigue and slowed delivery.

Define & Analyse. The objective was to reduce cognitive load and improve development flow. This use case aligned with a *low automation, high augmentation* strategy, using an IDE-integrated assistant combining **Generator** and **Reimaginator** functions. Risks included hallucinated suggestions, over-reliance by junior developers, and compliance with internal policies. Lightweight governance measures—peer review, IDE-only use, and developer-led control—were sufficient to mitigate these concerns.

Build-Measure-Learn. A Minimum Viable Implementation (MVI) was rolled out by enabling the assistant within existing IDEs. Feedback was gathered through informal team retrospectives. Developers reported improved task efficiency, smoother flow, and reduced friction during implementation, especially for repetitive or unfamiliar code. While experienced developers integrated the tool easily, junior developers required onboarding guidance. The assistant was retained for internal tasks, and prompt design documentation was improved in response to user feedback.

Use Case 2: Generating Wireframes from Prompts (Non-technical) Context. Product managers needed to quickly explore and communicate new feature ideas but were constrained by limited design resources.

Define & Analyse. The use case targeted faster visual prototyping and stakeholder alignment, following a *low automation, high augmentation* strategy. The tool combined **Generator** and **Reimaginator** features to produce mock-ups from text prompts. Risks included low fidelity, design inconsistency, and overconfidence in AI outputs. Because outputs were not externally shared, compliance and reputational risks were minimal.

Build-Measure-Learn. A lightweight pilot was launched with no technical integration. Product managers used the tool in discovery sessions to quickly generate wireframes, which were reviewed by designers before further development. The tool accelerated ideation and stakeholder input, reducing design bottlenecks. It was adopted as an optional step in the early discovery phase, supported by internal documentation on prompt crafting and clear expectations about output quality.

4.5 Limitations

This research is conceptual and illustrative in nature. Although the framework is grounded in literature and supported by real-world examples from a later-stage startup, these examples serve as demonstrations rather than formal validation. No user studies or multi-organization testing were conducted to evaluate the framework's effectiveness across diverse startup contexts. The application of the framework was retrospective and scoped internally, meaning its utility during live adoption processes or in earlier-stage startups remains untested. Additionally, the KPIs and evaluation metrics used in the case examples were mostly qualitative and based on informal feedback, rather than standardized measurement approaches.

Another limitation concerns the foundation on which the framework builds. As noted in the key findings, the original purpose of the Build-Measure-Learn (BML) loop lies in product validation and early-stage business model testing. While it has been extended in this work to support internal AI adoption processes, such a shift requires careful consideration. The assumptions that underpin BML—fast iteration, minimal investment, and clear product-market feedback—do not always transfer seamlessly to the complexities of internal technology adoption, particularly in the case of generative AI. This recontextualization may overlook challenges around change management, governance, and organizational learning that BML was never intended to address.

These limitations suggest opportunities for future work, including empirical validation through prospective studies, broader application in different organizational settings, and refinement of evaluation criteria to support more rigorous measurement. As a result, the generalizability of the framework and the level of confidence it provides for guiding decision-making in other startup contexts should be interpreted with caution.

5 Recommendations

For practitioners, particularly those in startup environments, the daBML framework aims to offer a lightweight structure to support the adoption of generative AI. Practitioners in this context include startup founders, product managers, innovation leads, and operations or engineering team members who are directly involved in evaluating and implementing new technologies. We do not present the framework as a complete solution, but rather as a tool to guide early framing, encourage risk awareness, and promote iterative learning. One key implication is to begin with strategic clarity instead of jumping directly into technical experimentation. Teams may benefit from asking what value they seek, what internal capabilities are available, and which processes could realistically benefit from AI. The early stages of the framework — *Define* and *Analyse* — are designed to support this reflection. They offer a way to surface risks and constraints before resources are committed. This may help avoid premature or misaligned deployments. In applying the framework, teams are encouraged to define KPIs early and use them to shape small-scale pilots. Importantly, daBML is not meant to be prescriptive. It should be adapted to the context, resources, and maturity level of the organization using it.

Although the use cases focus on a later-stage startup, the daBML framework may also be relevant for earlier-stage teams. Its lightweight structure and emphasis on scoping and early risk reflection could support intentional experimentation when resources are limited. However, very early-stage startups may require further adaptation, and future work could explore how the framework performs in less mature organisational settings.

For researchers, this work highlights the need for adoption models that reflect the speed, uncertainty, and constraints typical of startup settings. While daBML builds on the well-known Build-Measure-Learn loop, it introduces upstream elements that are often overlooked. These include early-stage framing, typology classification, and lightweight risk analysis. Future research could explore whether these additions improve adoption outcomes. Future work could include validation through empirical studies. This might involve testing the framework across different domains, startup sizes, or AI maturity levels. Action research or field studies could help refine its components and assess its practical value. There is also room to examine how startups define success in AI adoption—particularly beyond technical implementation. This includes questions around strategic alignment, organizational learning, and ethical use. The daBML framework may provide a starting point for that discussion.

6 Conclusion

This chapter introduces daBML, a process-oriented toolset to support the adoption of generative AI in startup environments. The framework builds on the Build-Measure-Learn (BML) cycle and adds two upstream stages — *Define* and *Analyse*. These additions aim to bring more structure to early framing and risk consideration, especially in contexts where generative AI adoption carries organizational and ethical complexity.

The framework draws from existing literature and is illustrated through practical use cases. However, it remains conceptual. Its scope is limited to a specific organizational setting, and it has not yet been validated through broader empirical research. Practitioners are encouraged to view it as a starting point—something to adapt and test in their own context, rather than as a fixed recipe.

Future work could examine how the framework performs in different startup types or industries. Studies may also focus on how teams apply the framework in real time: how they define impact, how risk assessments shape implementation, and how KPIs evolve throughout the process. These insights could help improve the framework's structure and usability.

More broadly, this work speaks to a wider need for lightweight, startup-sensitive approaches to AI adoption. daBML does not aim to solve this challenge entirely, but offers one contribution toward a more intentional and reflective adoption process—one that balances speed with strategic alignment and long-term value.

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