

## From Start-Up to Smart-Up: The Role of AI Maturity in Scaling UK Tech Startups

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**Abstract:** The growing influence of artificial intelligence in the startup world has sparked renewed interest in how early-stage ventures approach AI—not just in terms of adoption, but also in how they signal and structure that capability. While several models exist to measure AI maturity, most are geared toward large organizations and don't quite fit the realities of young, fast-moving startups. This study introduces a framework we call the Smart-Up Maturity Model (SMM), developed to assess AI maturity in startups based on what can be observed publicly across four practical areas: how AI is used in products, internal operations, team skills, and overall strategy.

We applied the model to 20 AI-focused startups in the UK and complemented this with qualitative insights drawn from founder interviews. The results point to a loose connection between AI maturity and factors like funding and team growth—but the patterns weren't always linear.

**Keywords:** AI maturity, Startups, Smart-Up Maturity Model, Digital transformation, UK AI strategy.

**Jel Classification Codes :** L26,M13,M15.

### Introduction:

Artificial Intelligence (AI) is no longer confined to large enterprises or research institutions; it is now playing a pivotal role in shaping the trajectory of startups. In the United Kingdom—a country actively positioning itself as a global leader in responsible AI innovation—the startup ecosystem is vibrant but uneven. While a growing number of startups claim AI as a core part of their identity, the extent to which

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AI is truly embedded in their operations and strategies varies considerably. This variation brings forward an important and underexplored research question: **How does the level of AI maturity influence a startup's ability to scale?**

To investigate this, we introduce the concept of the “Smart-Up”—a startup that has moved beyond experimentation and is integrating AI meaningfully across its core domains. To support this concept, we propose the Smart-Up Maturity Model (SMM), a framework designed to assess AI maturity through four dimensions: product integration, operational use, strategic orientation, and talent capability. The SMM accounts for the unique characteristics of startups—such as lean teams, fast iteration cycles, and limited access to internal data—by relying on publicly observable indicators rather than internal metrics.

This study employs a mixed-methods exploratory approach. We begin with a thematic analysis of four publicly available founder interviews to gain qualitative insight into how startup leaders perceive and pursue AI integration. This is followed by the application of the SMM to a purposive sample of 20 UK-based AI startups, using structured data collected from publicly accessible platforms like Crunchbase, LinkedIn, and company websites.

By linking different levels of AI maturity to observable growth indicators—such as funding, team size, and speed of market traction—we aim to examine whether greater maturity corresponds with stronger scaling potential. Our contribution lies in offering a framework that captures the complexity of AI adoption in startups and provides a practical tool for founders, investors, and policymakers to assess AI readiness in a fast-evolving innovation environment.

## **I.Literature Review**

The role of Artificial Intelligence (AI) in startup development has gained increasing scholarly attention, yet many existing frameworks fall short of capturing how AI is actually adopted and scaled in early-stage ventures. Startups operate under different conditions than large firms—they are typically lean, fast-moving, and resource-constrained. As a result, models developed for corporate environments often fail to reflect the realities of small, agile organizations trying to integrate AI while navigating uncertainty.

This review draws on five areas of literature that are particularly relevant to this study: (1) AI-driven innovation in startups; (2) existing AI maturity models; (3) conceptual groundwork for the Smart-Up Maturity Model (SMM); (4) scalability in startup contexts; and (5) the specific features of the UK's AI ecosystem.

### **1. AI in Startups: Ambition and Uneven Integration**

Startups are frequently described as ideal environments for experimenting with digital technologies, and AI is no exception. Prior research highlights the potential of AI to drive new business models, automate tasks, and enhance customer engagement (e.g., Nambisan, 2017; Agrawal et al., 2018). However, despite this promise, the depth of AI adoption among startups is inconsistent. Many ventures include AI in their branding or vision but rely on third-party tools or outsourced development, raising questions about the gap between projected and actual capability (Wamba-Taguimdje et al., 2020).

### **2. Existing AI Maturity Models: Structured but Ill-Fitting**

Several influential models—such as Gartner's AI Maturity Model and Deloitte's AI Maturity Index—have shaped thinking around how organizations evolve in their AI journey. These frameworks generally build on the Capability Maturity Model (Paulk et al., 1993), emphasizing a staged progression from experimentation to full integration. However, such models tend to assume formal organizational structures, stable teams, and consistent access to internal data. These assumptions limit their applicability to startups, which often face volatility, evolving roles, and data limitations (Duan et al., 2019; Vial, 2019).

### **3. Toward a Startup-Centric Maturity Framework**

The Smart-Up Maturity Model proposed in this study draws inspiration from earlier models but adapts them to the conditions typical of startups. The SMM retains the idea of staged progression but redefines what “maturity” looks like for ventures with small teams and limited resources. Instead of internal process audits, the model relies on publicly observable indicators, such as how AI is represented in products, team structures, and strategic communication. This approach is intended to be both practical and scalable for use by researchers, investors, and support organizations.

### **4. Scalability: Missing Links Between Maturity and Growth**

The concept of scalability is central in entrepreneurship literature, yet

relatively little has been written about how AI maturity affects a startup’s ability to grow. While investment in AI startups has surged—often based on perceived innovation—the relationship between real capability and growth outcomes remains underexplored. Some studies suggest that startups receiving significant funding may not necessarily have advanced internal systems, highlighting a gap between perceived and actual maturity (Picken, 2017; Tech Nation, 2020).

**5. The UK Context: Opportunity and Fragmentation**

The UK government’s AI strategy emphasizes responsible development, skills, and innovation support. Institutions like the Alan Turing Institute and Innovate UK are backing AI-focused startups through funding and infrastructure. However, as noted by Nesta (2022) and the Royal Society (2021), there is often a disconnect between policy goals and the varied realities of early-stage firms. While some receive national attention, many remain under-resourced or loosely integrated. This makes it especially important to have a flexible maturity model that can assess where startups truly stand, beyond surface-level AI claims.

In sum, this review highlights a clear need for a maturity model tailored to the startup environment—one that captures how AI is actually being used, not just how it is discussed. The Smart-Up Maturity Model aims to respond to this need by offering a lightweight but structured way to evaluate maturity using signals that are externally visible and practically accessible.

**II.Methodology**

This study adopts a mixed-methods exploratory design to investigate how AI maturity manifests within UK-based startups and how it may relate to their capacity for scalability. The dual objectives are: (1) to refine and test the Smart-Up Maturity Model (SMM) in the context of early-stage ventures, and (2) to examine how observable indicators of AI maturity align with measurable signs of startup growth. This approach was chosen to balance conceptual development with empirical analysis, leveraging both qualitative and quantitative data.

| 1.                                                                                                                                | Research | Design | Overview |
|-----------------------------------------------------------------------------------------------------------------------------------|----------|--------|----------|
| The study is structured around two complementary components. The first involves a thematic analysis of publicly available founder |          |        |          |

interviews, with the aim of uncovering how startup leaders articulate their AI strategies and operational decisions. The second component consists of comparative case profiling across a sample of 20 startups, drawing on publicly accessible secondary data to apply the SMM framework and explore patterns related to scaling indicators.

Table (1) : Methodology Design Table

| Component    | Purpose                                                                  | Methodology                                      |
|--------------|--------------------------------------------------------------------------|--------------------------------------------------|
| Qualitative  | To understand how founders frame their AI integration journey            | Thematic analysis of selected founder interviews |
| Quantitative | To examine links between maturity levels and startup scalability metrics | Structured case profiling using public data      |

**Source:** Author’s elaboration based on mixed-methods frameworks (Braun & Clarke, 2006; Duan et al., 2019) and SMM application protocol.

This dual approach enables both inductive exploration and systematic comparison, ensuring that the SMM is informed by real-world narratives as well as observable startup performance.

2. Conceptual Foundation: The Smart-Up Maturity Model (SMM)

The Smart-Up Maturity Model (SMM) draws on established frameworks such as the Capability Maturity Model (Paulk et al., 1993), Gartner’s AI Maturity Model (2020), and Deloitte’s AI Maturity Index (2019). While these earlier models assume stepwise, structured capability development suited to large organizations, they are less applicable to startups, which operate with fluid teams, flexible processes, and rapid decision-making.

To address this gap, the SMM adapts the staged logic of traditional models to the startup context. It defines five levels of AI maturity—from AI-Naive (Level 1) to AI-Led (Level 5)—assessed across four core dimensions: product integration, operational use, strategic orientation, and talent capability. The model relies solely on publicly available data (e.g., company websites, media coverage, founder interviews), ensuring transparency and scalability for comparative research and investor evaluation.

Maturity classification follows a structured scoring system, where a startup is placed at a given level if it meets at least three of the four criteria associated with that stage. This flexible approach allows

for partial or uneven progress across dimensions while preserving consistency and analytical rigor.

### **3. Qualitative Component: Thematic Interview Analysis**

The qualitative portion of the study focuses on understanding how founders narrate their AI journey—both in terms of strategic intent and practical implementation. To that end, four publicly available interviews were selected using the following criteria:

The interview featured a UK-based startup founder or senior executive

The company was actively using or developing AI technologies

The discussion addressed at least one of the SMM dimensions (e.g., talent, product, strategy)

These interviews, sourced from podcasts and online media platforms, were transcribed and analyzed using Braun and Clarke's (2006) six-phase method for thematic analysis. Themes were generated inductively and then interpreted through the lens of the SMM to assess how founders' lived experiences align with the maturity model's categories and indicators.

### **4. Quantitative Component: Comparative Startup Profiling**

For the quantitative phase, a purposive sample of 20 AI-focused startups was constructed. Inclusion criteria were as follows:

Publicly self-identified as AI-enabled or AI-led

Founded between 2015 and 2023

Sufficient public information available to score SMM dimensions

The selected startups represent a spectrum of maturity levels (Levels 2 to 5), intentionally excluding Level 1 (AI-Naive) firms to ensure relevance to the research question. The data collection process relied on multiple public sources, including:

Crunchbase, Dealroom, and Companies House (for funding and founding data)

Company websites and media coverage (for product integration and strategic orientation)

LinkedIn and team pages (for talent capability)

Founder interviews, blogs, or speeches (for insight into AI vision and execution)

The following variables were compiled for each firm:

SMM maturity level

Total public funding (in GBP)

Startup age (based on founding year)

Reported team size

Most recent funding round (e.g., Seed, Series A)

## 5. Application of the SMM Framework

Each startup was evaluated using a standardized scoring matrix aligned with the SMM structure. Maturity classification was assigned when a company met three out of four indicators for a specific level. Where interpretation was required, data were triangulated across sources to enhance reliability. Firms that lacked sufficient evidence were excluded from scoring.

The evaluation excluded Level 1 firms by design, focusing instead on ventures that had at least signaled some level of AI engagement. The resulting sample included:

Level 2 (AI-Aware): Limited implementation, mainly visionary or branding

Level 3 (AI-Adopting): Early-stage application of third-party tools

Level 4 (AI-Embedded): AI supporting key product or operational processes

Level 5 (AI-Led): AI deeply integrated across product, strategy, and team capability

## 6. Ethical Considerations

All data used in this study were gathered from publicly accessible sources. No private, confidential, or proprietary data were collected. All quoted material was attributed to publicly published interviews, and company evaluations were based on information that is available in the public domain. The researcher has no affiliation or financial interest in any of the firms profiled, and the research was conducted in line with the ethical standards for secondary data analysis.

## 7. Limitations and Reflexivity

Several limitations are acknowledged. First, talent capability was the most challenging dimension to assess, due to the limited public visibility of team roles. LinkedIn data and job postings were used as proxies. Second, funding data may underrepresent bootstrapped or stealth-mode ventures. Third, while a structured scoring system was applied, interpretive judgment was still required in borderline cases. Steps such as source triangulation and explicit scoring rules were implemented to minimize subjectivity.

The researcher acknowledges their dual role in both constructing and applying the SMM framework, which introduces the potential for confirmation bias. However, transparency in methods and a clear separation between conceptual development and empirical application were maintained to mitigate this risk.

Overall, the methodology presented here allows for a systematic, transparent, and scalable way to evaluate AI maturity in startups using publicly accessible data. The approach is intended to be both conceptually grounded and practical for use by researchers, investors, and innovation policymakers.

III.Results and Discussion

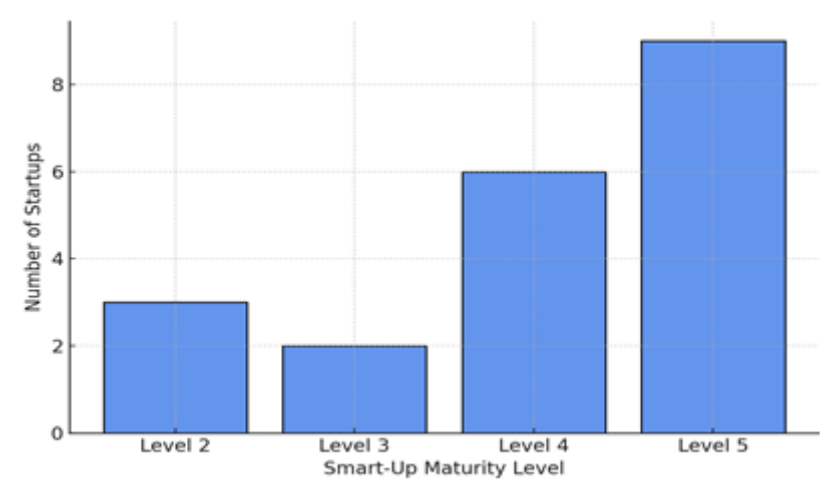
5.1 Distribution of AI Maturity Levels

Table (2): Distribution of Startups by SMM Level

| SMM Level | Label             | Definition                                | Number of Startups |
|-----------|-------------------|-------------------------------------------|--------------------|
| Level 2   | AI-Aware          | Mentions AI in mission/branding only      | 3                  |
| Level 3   | AI-Adopting       | Basic tool usage, low integration         | 2                  |
| Level 4   | AI-Embedded       | AI supports product or ops, some talent   | 6                  |
| Level 5   | AI-Led (Smart-Up) | AI central to strategy, team, and product | 9                  |

Source: Author’s analysis using the Smart-Up Maturity Model, adapted from Capability Maturity Model Integration (CMMI), Gartner (2020), and Vial (2019).

Figure 1 – Number of Startups by AI Maturity Level (SMM)



**Source:** Visualized from Table (2). Data compiled by the author using the Smart-Up Maturity Model applied to 20 UK startups.

The application of the Smart-Up Maturity Model (SMM) to 20 UK-based AI startups revealed a spread across four of the five maturity levels: three at Level 2 (AI-Aware), two at Level 3 (AI-Adopting), six at Level 4 (AI-Embedded), and nine at Level 5 (AI-Led). Level 1 (AI-Naive) startups were excluded to focus on firms with observable AI engagement. This distribution confirms the SMM’s effectiveness in differentiating degrees of AI integration and supports critiques of traditional linear models such as the Capability Maturity Model (Paulk et al., 1993) and Gartner’s AI Maturity Model (2020). Consistent with findings by Vial (2019) and Duan et al. (2019), the data illustrates that startup maturity evolves non-linearly, influenced by contextual, strategic, and market factors.

The predominance of Level 5 firms may partly reflect a visibility bias, as such startups are more likely to attract investor attention, media coverage, and inclusion in public databases. Yet, the coexistence of Level 2 and Level 3 firms within the same ecosystem highlights the persistence of superficial AI adoption or “AI washing” (Wamba-Taguimdje et al., 2020), where AI serves more as a branding device than as a genuine capability. The SMM’s multidimensional framework—assessing product integration, operational use, strategic orientation, and talent capability—helps reveal such inconsistencies, distinguishing between startups that outsource AI development and those that build in-house expertise. This makes the SMM a valuable diagnostic tool for analyzing heterogeneous AI implementation across startup environments.

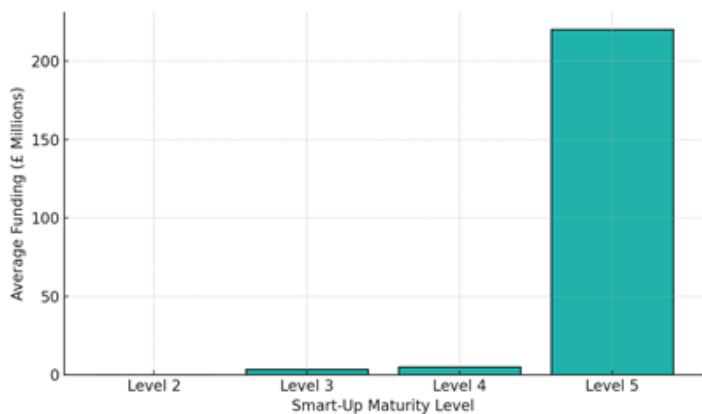
5.2 AI Maturity and Funding Patterns

Table (3): Average and Median Funding by SMM Level

| SMM Level | Average Funding (£M) | Median Funding (£M) | Number of Startups |
|-----------|----------------------|---------------------|--------------------|
| Level 2   | 0.00                 | 0.00                | 3                  |
| Level 3   | 3.40                 | 3.40                | 2                  |
| Level 4   | 4.97                 | 5.50                | 6                  |
| Level 5   | 220.22               | 75.00               | 9                  |

Source: Funding data compiled from Crunchbase and TechCrunch reports (2022–2023) on selected UK AI startups.

Figure 2 – Average Funding by AI Maturity Level (SMM)



**Source:** Derived from Table (3) Funding data from Crunchbase and TechCrunch reports on UK AI startups (2022–2023)

The analysis of the relationship between AI maturity and access to capital reveals clear disparities across the Smart-Up Maturity Model (SMM) levels. Startups at Level 5 reported an average funding of £220.22 million (median £75 million), compared with £4.97 million for Level 4, £3.4 million for Level 3, and no recorded funding for Level 2. Although this pattern appears to show that higher maturity correlates with greater investment, the relationship is more complex. A few outliers—such as Wayve and Tractable—secured exceptionally large rounds due to the high capital demands of their sectors, thus skewing the averages. Median figures therefore provide a more balanced perspective.

Beyond these anomalies, the data indicates a feedback mechanism where maturity and funding mutually reinforce each other. Greater maturity increases investor confidence and attracts more capital, while financial resources enable further technological integration and team expansion, enhancing maturity in turn. However, as Duan et al. (2019) note, abundant resources may sometimes inflate perceptions of capability, making it difficult to gauge true maturity from external indicators alone.

The absence of significant funding among Level 2 startups highlights how investors are becoming more discerning, favoring firms that demonstrate genuine AI integration over those using AI as a superficial label. This finding underscores the relevance of the SMM as a tool for distinguishing between authentic AI-driven ventures and

those still in the aspirational phase, thereby refining investment evaluation criteria.

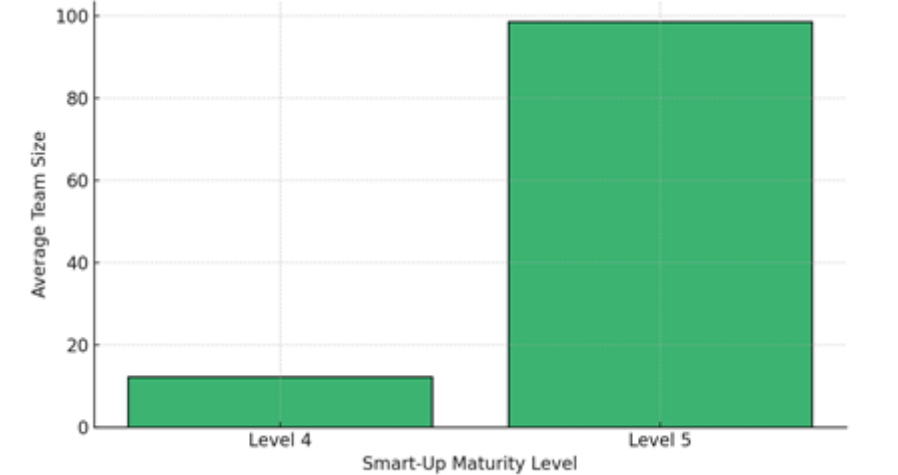
5.3 AI Maturity and Team Size

Table (4): Team Size by AI Maturity Level

| SMM Level | Average Team Size | Median Team Size | Number of Startups |
|-----------|-------------------|------------------|--------------------|
| Level 4   | 12.3              | 12               | 3                  |
| Level 5   | 98.6              | 85               | 7                  |

**Source:** Team size data gathered from LinkedIn company profiles, PitchBook, and official startup hiring pages, where publicly available.

Figure 3 – Average Team Size by AI Maturity Level (SMM)



**Source:** Derived from Table (4) Public data retrieved from LinkedIn company profiles and startup websites.

The analysis of team size, used as a proxy for internal capability and operational depth in AI-related functions, revealed a clear distinction across maturity levels. Level 4 startups had an average of around 12 employees, whereas Level 5 firms averaged nearly 99 employees, with a median of 85—indicating that higher AI maturity often coincides with a larger and more specialized workforce. However, several Level 5 firms demonstrated advanced maturity with fewer than 50 employees, emphasizing that alignment across the SMM’s four dimensions—AI ownership, product integration, and strategic coherence—can compensate for smaller size. Thus, while team size correlates with maturity, it is not a decisive indicator; team composition and expertise deployment matter more.

In contrast, data collection was more difficult for Level 2 and Level 3 startups, which often operate in stealth mode, rely on distributed or

outsourced teams, and display limited public transparency. This reinforces the challenge of measuring early-stage AI maturity through open data due to information asymmetry and inconsistent reporting. As Duan et al. (2019) note, early digital transformation tends to be informal and founder-driven, reducing the reliability of metrics such as headcount. The SMM mitigates these limitations by incorporating qualitative indicators and using multidimensional evaluation, ensuring that team size is interpreted contextually rather than as an isolated proxy for maturity.

#### **5.4 Themes from Founder Interviews**

##### **Theme 1: Strategic Vision – From Buzzword to Core Business Logic**

The study reveals a clear difference in how startups at various stages of the Smart-Up Maturity Model (SMM) integrate artificial intelligence (AI) into their strategy. For Level 5 companies, AI is not an added feature but a core element of their identity and value creation. Their founders describe AI as central to both the product design and the business model, illustrating what Gartner (2020) defines as a transformational orientation—where AI drives innovation rather than efficiency alone. In such firms, the product, team, and vision are inseparable from AI technologies, fully justifying their classification as “AI-Led.”

By contrast, startups at lower maturity levels, such as those in Level 2 (AI-Aware), tend to approach AI more as an aspiration than an operational reality. They often present AI as part of their branding or long-term vision, without yet possessing the technical structure or resources to implement it effectively. This gap between ambition and execution highlights that awareness of AI’s potential does not equate to integration or maturity.

These observations demonstrate that the SMM helps distinguish between startups that truly embed AI into their strategic fabric and those still developing the necessary capabilities. Moreover, the data challenge the assumption that startups necessarily evolve through the model’s levels in sequence. Some, like O’Meara’s firm, can be “born AI-Led,” integrating AI from inception, while others gradually work toward that state. This variation supports critiques of linear maturity models and emphasizes the importance of analyzing AI adoption in relation to each startup’s founding vision and developmental path.

## Theme 2: Talent Constraints – Building AI from the Inside Out

A second dominant theme that surfaced across the founder interviews was the role of AI-specific talent in enabling—or, quite often, delaying—progress toward higher maturity levels. The Smart-Up Maturity Model explicitly includes “Talent Capability” as one of its four core dimensions, based on the premise that human capital is not merely a functional resource, but a structural pillar in implementing AI meaningfully. The interviews supported this view, confirming that talent is both a practical constraint and an indicator of overall maturity.

Startups operating at lower levels of the SMM frequently described a significant gap between their strategic ambitions and their capacity to execute those ambitions internally. In her *TechRound* interview, Evgeniia Megrian reflected on this from the perspective of her early-stage EdTech startup:

“We had big ideas around AI automation, but the truth is, we were outsourcing most of it. We didn’t have the in-house expertise—and we couldn’t afford it.”

This quote illustrates her company’s SMM Level 2 classification clearly: AI played a central role in the startup’s vision, yet internal technical capabilities were limited or absent. Outsourcing served as a temporary solution, but it also reinforced dependency and restricted the speed at which the company could develop authentic internal maturity. This reflects Duan et al.’s (2019) observation that, for many small and medium-sized enterprises, AI remains an externalized function—managed by vendors or partners, rather than built into the firm’s learning and development structure.

In contrast, Mark Chaffey, CEO of Hackajob (assessed at SMM Level 4), provided a narrative that represented a transitional stage in talent development. Speaking on *The Marketing Rules Podcast*, he recalled: “We had the AI logic scoped early, but implementing it meant finding people who could build responsibly. That took time—and honestly, we had to grow into it.”

Chaffey’s account points to what might be described as a “maturity catch-up loop,” in which strategic vision and technical architecture are conceived early, but the formation of a qualified team lags behind. Over time, Hackajob succeeded in building its internal capabilities—particularly in areas like model validation and bias mitigation—but

this development occurred only after the company had achieved product-market fit. This case demonstrates how startups may straddle multiple dimensions within the SMM, scoring highly in product or strategy while remaining underdeveloped in talent during earlier stages.

At the upper end of the maturity spectrum, Sachin Dev Duggal, CEO of Builder.ai (rated at Level 5), offered a different perspective entirely. During his appearance on the *UKTN Podcast*, he described a deliberate, strategic commitment to building AI capability internally:

“We didn’t want to rely on outside models forever. We had to bring AI capability in-house—not just for innovation, but for control.”

Duggal’s statement reflects a deeper philosophy: that owning AI talent is essential not just for technical innovation, but for strategic autonomy. This mindset aligns with Gartner’s perspective that AI-led organizations must not only possess technical systems but embed talent development into both their operational and strategic layers. In Duggal’s case, talent was viewed as a competitive safeguard as much as a growth enabler.

The contrast between these three narratives underscores the complexity of talent maturity. It’s not merely about whether a firm has hired data scientists—it’s about how and when those capabilities are developed, and whether they are treated as external solutions or internal competencies. Some startups postpone AI hiring until investment rounds enable it, while others view building in-house expertise as a prerequisite for scaling. The SMM allows for the evaluation of this philosophy as a signal of maturity in its own right, going beyond product features to assess whether the organizational backbone can support long-term innovation and resilience.

### **Theme 3: Credibility Signaling – When Saying “AI” Isn’t Enough**

Another major finding from the founder interviews highlights the growing pressure on startups to demonstrate real AI maturity to external stakeholders such as investors and clients. Founders across all Smart-Up Maturity Model (SMM) levels agreed that the term “AI” has become overused, and that credibility now depends on demonstrable capability rather than marketing claims.

For startups at lower maturity levels (e.g., Level 2), this tension is especially strong. As Evgeniia Megrian explained about her early EdTech venture, labeling a company “AI-powered” may attract early

attention, but it fails under due diligence. This gap between rhetoric and technical reality mirrors the phenomenon of “AI-washing” (Wamba-Taguimdje et al., 2020), where startups overstate AI use to appear more innovative. At this stage, the credibility deficit becomes visible during funding negotiations or client assessments.

In contrast, Level 4 and Level 5 startups treat credibility as a function of transparency and evidence. Mark Chaffey of Hackajob (Level 4) described building dashboards and explanatory tools to show algorithmic performance—shifting from hype to visible, verifiable value. This marks a transition from rhetorical signaling to demonstrable impact, making trust an operational outcome rather than a communication strategy.

At the highest maturity level, credibility becomes institutionalized within company culture. Sachin Dev Duggal of Builder.ai (Level 5) stressed that claiming to be “AI-powered” is no longer enough; firms must prove and demonstrate their systems through prototypes, metrics, and transparent workflows. Here, AI maturity is expressed through systematic delivery and verification, not slogans.

The Smart-Up Maturity Model is particularly effective in assessing this evolution because it focuses on publicly observable signals—such as team structure, product design, and communication—capturing not only what startups build but also how they make their AI capabilities credible to the outside world.

#### **Theme 4: Ethical Friction – The Case for Responsible AI as a Fifth Dimension**

A final theme emerging from the founder interviews concerns the tension between the speed of startup execution and the requirements of responsible AI development. While ethics are often discussed in academic or policy settings, several founders in this study emphasized that ethical maturity has become a practical constraint on product design—especially in sensitive, high-impact sectors.

Evgeniia Megrian highlighted the risks of ignoring safeguards like fairness and transparency, warning that the pressure to scale quickly can lead to large-scale harm. Her reflection echoes the concept of “ethical debt” (Raji et al., 2020), which describes the long-term risks—regulatory, reputational, and operational—created when startups neglect fairness or accountability early in development. Even

companies at the AI-Aware stage (SMM Level 2) recognize these ethical stakes, though they often lack the means to act on them.

At a higher level of maturity, Sachin Dev Duggal of Builder.ai (Level 5) illustrated what embedded ethical governance looks like in practice. For him, responsible AI is not abstract or external but built directly into testing, model evaluation, and client onboarding. This approach reflects a systems-level understanding of AI ethics—one increasingly supported by policy actors like the UK Department for Science, Innovation and Technology (DSIT, 2023).

However, the study also found inconsistency among startups at similar maturity levels: while some integrated ethics into their core operations, others—especially in fields like recruitment or marketing automation—acknowledged ethical issues but prioritized speed and performance. This uneven commitment points to a broader governance gap in the AI startup ecosystem.

Given these findings, the research suggests that the Smart-Up Maturity Model (SMM), which currently includes four dimensions (product, operations, strategy, and talent), should be expanded to include a fifth dimension: ethical maturity or AI governance. This would allow assessment of fairness audits, explainability mechanisms, risk mitigation, and stakeholder engagement as indicators of responsible AI practice.

Ultimately, ethical maturity is emerging as a defining marker of advanced AI startups, not only as a tool for risk management but as a foundation for long-term credibility and trust. Startups that overlook ethical capability risk falling behind evolving regulatory frameworks and public expectations, reinforcing the need for the next version of the SMM to formally integrate ethics as a key dimension of AI maturity.

### **5.5 Integration and Model Tensions**

Taken together, the findings confirm that the Smart-Up Maturity Model (SMM) is a valuable framework for identifying and distinguishing different levels of AI integration among early-stage startups. Firms positioned at higher maturity levels generally had greater access to capital, larger teams, and stronger alignment between their AI capabilities and overall business strategies. These patterns, observed in both quantitative and qualitative data, suggest that the

SMM is not only conceptually sound but also empirically responsive to real variations in startup behavior and structure.

Nevertheless, the study also uncovered several complexities that challenge a linear interpretation of the model. Many startups demonstrated uneven maturity across the SMM's four dimensions, showing strength in areas such as product integration or strategic alignment but weakness in talent development or operational use. This asymmetry raises questions about whether maturity should be seen as a cumulative process or as a combination of independent competencies, since some firms performed well in certain aspects while remaining immature in others.

Furthermore, the progression through the SMM levels was not always sequential. In some cases, such as that of Matthew O'Meara's company, a startup appeared to be "born AI-led," integrating advanced maturity features from the outset rather than evolving gradually. This observation challenges the assumptions of earlier frameworks like the Capability Maturity Model (CMM), which depict growth as a step-by-step process. For ventures founded by experienced AI professionals or supported by early capital, the path to maturity may thus be more immediate and less incremental.

The research also revealed that the relationship between AI maturity and investment is mutually reinforcing rather than one-directional. While mature firms tend to attract more funding, financial resources can also accelerate maturity by enabling the recruitment of skilled talent, the acquisition of proprietary models, or the development of custom infrastructure. This reciprocal relationship complicates any clear causal inference: maturity may bring investment, but investment equally helps build maturity.

Another limitation lies in the absence of a specific ethical or governance dimension within the current version of the SMM. Although some Level 5 startups adopted advanced responsible AI practices, others neglected these considerations entirely. Without a formal ethical category, the model may overestimate maturity in firms that demonstrate technical sophistication but lack adequate safeguards—an issue that could become increasingly significant as regulations tighten in sensitive sectors such as healthcare, hiring, or education.

Finally, the reliance on public data for scoring introduces both inclusivity and inaccuracy. On the one hand, this approach allows the model to be applied widely by investors, policymakers, and researchers without requiring internal access. On the other hand, it can lead to blind spots: stealth startups or those that minimize AI in their public communication may be underrated, while firms that exaggerate their capabilities in marketing may be overrated.

Overall, the study emphasizes that the SMM should be used as a diagnostic tool rather than a strict ranking system. Its real value lies in revealing the diverse ways startups engage with AI—not just in their claims, but in how AI is integrated across products, people, strategy, and operations. When applied with contextual understanding and interpretive flexibility, the model offers a practical and scalable method for assessing AI maturity in an innovation landscape characterized by uneven resources and noisy signals.

## **5.6 Implications**

This study provides important implications for understanding and guiding AI adoption within startup ecosystems, especially in contexts like the UK where innovation policy, investment, and entrepreneurship are closely intertwined. Through the development and application of the Smart-Up Maturity Model (SMM), the research advances the theoretical and practical conversation beyond simplistic distinctions between “AI” and “non-AI” startups, instead framing AI capability as a staged and multidimensional process.

From a theoretical standpoint, the SMM offers a valuable middle ground between abstract digital transformation models and rigid, linear maturity frameworks. The findings confirm that AI maturity among startups is non-linear, shaped by factors such as founder intent, market timing, and access to capital. Some ventures emerge with AI capability integrated from inception (“born mature”), while others evolve gradually. This supports prior research by Vial (2019) and Duan et al. (2019), emphasizing that small firms follow distinct innovation trajectories. Moreover, the SMM’s four-dimensional structure—encompassing product integration, operational use, strategic orientation, and talent capability—translates maturity into observable, measurable criteria, enabling cross-sectoral and comparative studies on AI adoption.

From a practical perspective, the model serves as a diagnostic and decision-support tool for multiple stakeholders. For founders, it enables self-assessment and strategic prioritization by identifying which dimensions require development. For investors, it functions as a screening framework to distinguish between genuine AI-driven ventures and those engaging in “AI-washing,” enhancing due diligence and capital efficiency. For policymakers and innovation bodies, the model offers a scalable, non-intrusive method to assess ecosystem maturity, guide funding programs, and track national progress. It also establishes a shared vocabulary that connects technical, entrepreneurial, and regulatory perspectives on AI readiness.

Overall, the Smart-Up Maturity Model contributes both conceptually and operationally to a richer understanding of how AI capability develops within startups—highlighting that true maturity involves not only technological sophistication, but also strategic alignment, organizational learning, and transparency.

### **5.6.3**

### **Future**

### **Extensions**

Finally, the model’s current four-dimension structure may be expanded in future work to include ethical maturity as a fifth category. As discussed earlier, responsible AI practices—such as fairness testing, explainability protocols, and stakeholder engagement—are becoming critical indicators of trustworthiness and long-term viability. Integrating such elements would enhance the model’s relevance as AI regulation tightens and public scrutiny grows.

## **6. Conclusion**

This study sought to fill a crucial gap in understanding and evaluating AI maturity within early-stage startups. Existing enterprise-oriented models often assume levels of scale, structure, and visibility that do not apply to startups. To address this, the research introduced the Smart-Up Maturity Model (SMM)—a multidimensional framework assessing AI maturity through publicly observable indicators across four dimensions: product, operations, strategy, and talent.

Applying the SMM to 20 UK-based AI startups, complemented by founder interviews, yielded three major insights. First, AI maturity among startups is non-linear and heterogeneous,

reflecting differences not only in the extent of AI use but also in its strategic consistency. Second, maturity reflects both capability and credibility—some startups authentically implement AI, while others merely signal it. Third, the analysis revealed emerging aspects such as ethical maturity, suggesting areas for future refinement of the model as AI governance expectations evolve.

The SMM also offers practical applications: it serves as a diagnostic tool for founders to assess progress, a screening framework for investors and policymakers to gauge AI credibility, and a research foundation for comparative and longitudinal studies. Despite limitations—such as reliance on public data and equal weighting across dimensions—the model represents a significant step toward a more contextual and nuanced understanding of AI maturity in startups, bridging the gap between aspiration and genuine integration.

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