Challenges and Mitigation Strategies for AI Startups: Leveraging Effectuation Theory in a Dynamic Environment

Research Paper

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Abstract. Investments in AI startups have surged in recent years, with significant backing from both major tech corporations and private investors supporting ventures that center artificial intelligence in their products. While AI startup founders bring innovative ideas that offer distinct value to customers, they also face challenges unique to their field. To identify the specific benefits and obstacles AI startups encounter, this study adopts a qualitative research approach, conducting ten semi-structured interviews with founders from the DACH region, complemented by a literature analysis. Findings reveal that issues such as data acquisition, talent recruitment, AI model development, regulatory hurdles, and competition, as well as navigating a highly uncertain environment, vary widely across AI startups and are influenced by company-specific factors. Based on these insights, we apply effectuation theory to explore potential strategies for overcoming these challenges. The study further extends the existing literature on startup development in high-tech fields.

Keywords: Artificial intelligence, Entrepreneurial challenge, Effectuation theory, Qualitative research

1 Introduction

Artificial Intelligence (AI) is transforming businesses and society by driving productivity gains through business augmentation, automation, and a vast array of innovative applications (Berente et al., 2021; Weber et al., 2022). Nearly 75% of the world's largest organizations now consider AI crucial to their competitive advantage, as its integration has shown to enhance sales and market value (Babina et al., 2024). As AI advances, new ventures centered on AI solutions are rapidly emerging, leveraging the technology's capacity for automation, predictive insights, and real-time data processing to create disruptive products across diverse sectors (Chalmers et al., 2021; McGrath, 2024). Those "AI startups" serve as catalysts for innovation, embedding advanced AI into their software products and playing an essential role in reshaping the business landscape. High-profile funding rounds, such as OpenAI's record-breaking \$11.3 billion investment in 2024, underscore the immense importance that investors

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and tech giants attribute to these ventures, positioning them as integral drivers of economic transformation (Babina et al., 2024).

Despite their potential (Short & Short, 2023), AI startups face significant uncertainty due to the novelty of AI technology and the lack of historical precedents. This uncertainty is underscored by the rapid evolution of the field and limited theoretical guidance, presenting unique challenges for founders (Shepherd & Gruber, 2021). Scholars agree that effectuation is more commonly applied in digital environment (Cai et al., 2017; Nambisan, 2017; Zaheer et al., 2022), especially in early stages to reduce uncertainty (Cai et al., 2017). Addressing this research gap, the following study seeks to provide valuable insights into the challenges AI startups encounter (van Gelderen et al., 2021) and explore how these can be mitigated through effectuation theory (Sarasvathy, 2001). Zaheer et al. (2022) as well as Yrjönkoski and Suominen (2018) emphasize the importance of a strong network for the survival and growth of digital startups, according to effectuation (Sarasvathy, 2001).
Specifically, it aims to answer the following research question:

RQ) What challenges do AI startups face, and how can these be addressed using effectuation theory?

This study bridges the fields of entrepreneurship and information systems by examining the distinct challenges faced by AI startups – a venture type characterized by high uncertainty, heavy data dependency, regulatory ambiguity, and rapidly evolving technical requirements (Weber et al., 2022; Schulte-Althoff et al., 2021). Although AI startups often operate within the broader digital ecosystem, their reliance on machine learning models, talent scarcity, and exposure to AI-specific regulations (e.g., EU AI Act) create fundamentally different entrepreneurial conditions compared to traditional digital startups. Current literature tends to group AI startups with other digital ventures, thus overlooking these domain-specific challenges. This study addresses this gap by problematizing the implicit assumption of similarity and providing a theoretically grounded framework to differentiate AI startups from general digital ventures.

To achieve these insights, we employ a qualitative approach, using ten semi-structured interviews with eleven AI startup founders to uncover rich, context-specific insights grounded in real-world practices. A qualitative approach allows for an in-depth exploration (Bryman & Bell, 2015) of the nuanced challenges, experiences, and decision-making processes unique to AI startups.

The paper begins by introducing effectuation theory, its relevance to digital business models, and AI startup characteristics. Next, the methodology is detailed, followed by a presentation of the results. The discussion section examines findings and connects them with prior literature, outlines study limitations, and suggests future research directions.

2 Theoretical Background

2.1 Effectuation Theory

Schumpeter (1942) describes an entrepreneur as a revolutionary force in capitalism, driving economic change through innovation. Shane and Venkataraman (2000) define entrepreneurship as capitalizing on profitable opportunities. After assessing opportunities, entrepreneurs typically design Business Models (BMs), guided by frameworks from scholars like Osterwalder and Pigneur (2010). They operate under uncertainty, producing new products or services with limited constraints (Zahra, 2021). The BM captures value creating and delivery, which is refined through iterative testing (Osterwalder & Pigneur, 2010). Effective BMs are crucial in nascent markets with novel structures and incomplete products (McDonald & Eisenhardt, 2020) such as the AI market. In nascent markets entrepreneurs should be self-focused, continuously learning from competitors, rather than try to distinguish themselves (McDonald & Eisenhardt, 2020).

Sarasvathy (2001) suggests that effectuation would be suited for startups in nascent markets, where reliable predictions are impractical due to limited data (Sarasvathy, 2001) such as the internet market. Although this example may now seem outdated, the digital landscape remains uncertain with new markets emerging from ongoing developments (Leong et al., 2016). Digital markets are dynamic, requiring evolving entrepreneurial approaches (Nambisan, 2017). Further, digital products are developed agile, with rapid trial-and-error cycles (Zaheer et al., 2022). The flexible BM, supported by the modularity of digital technologies (Zaheer et al., 2022) and the unique challenges of digital environments (Leong et al., 2016), such as uncertainty, rendering of predetermined opportunities and goals and frequent fluctuations in cost, make effectuation particularly applicable in this environment (Nambisan, 2017).

Effectual venture creation begins by evaluating available means, such as the entrepreneur's attributes, network, and resources (Sarasvathy, 2001). Actions are then identified, with goals continuously adjusted on evolving means, requiring a short-term focus (Sarasvathy, 2001).

Sarasvathy (2001) defines five key principles of effectuation which are presented in Table 1. While the first four principles, offer concrete decision-making heuristics, the fifth – Pilot-in-the-Plane – reflects the overarching logic of control that underpins effectual reasoning.

Table 1. Key principles of effectuation (based on Sarasvathy, 2001)

Principle	Description
Bird-in-Hand	Entrepreneurs initiate ventures using their existing means – namely, who they are, what they know, and whom they know.
Affordable Loss	Decisions are guided by the potential downside the entrepreneur is willing to bear, rather than projected returns.
Crazy Quilt	Partnerships are formed with self-selected stakeholders, enabling co-creation and access to complementary resources.
Lemonade	Unexpected events and contingencies are leveraged as opportunities to innovate, rather than seen as setbacks.
Pilot-in-the Plane	Entrepreneurs focus on exerting control over the future through their own actions, rather than relying on prediction.

2.2 AI Startups

While digital entrepreneurship has been widely studied (Nambisan, 2017; Zaheer et al., 2022), AI startups exhibit distinct characteristics that warrant separate theoretical consideration. Unlike traditional software startups, AI ventures operate in highly uncertain environments due to algorithmic opacity, emergent model behavior, and dependence on complex data ecosystems (Townsend et al., 2024; Wang et al., 2022). These ventures face unique challenges around data acquisition, AI talent scarcity, and compliance with domain-specific regulatory frameworks such as the EU AI Act (Bessen et al., 2022; Mahendra, 2023). Their innovation cycles are shaped by continuously learning systems and reliance on external platforms – factors less typical in conventional digital ventures (Schulte-Althoff et al., 2021; Weber et al., 2022).

Although some AI startups adopt business models similar to those of SaaS firms, the integration of AI often transforms their value proposition and operational logic (Garbuio & Lin, 2019). These distinct strategic, technical, and regulatory conditions align AI ventures with McDonald and Eisenhardt's (2020) view of nascent markets marked by high uncertainty and evolving norms (Berente et al., 2021).

This paper takes the position that AI startups constitute a novel subcategory of digital ventures that require tailored theoretical and empirical investigation – particularly with respect to how they navigate uncertainty, make strategic decisions, and mobilize scarce resources. To address this gap, we apply effectuation theory as a lens to analyze the challenges faced by AI startups and explore how founders respond in dynamic environments. Despite increasing interest in AI entrepreneurship, its conceptual integration with effectuation theory remains underexplored.

3 Research Design

We adopted a qualitative research design (Bryman & Bell, 2015) focusing on exploring behavioral patterns and experiences of AI startup founders through the lens of effectuation (Sarasvathy, 2001).

3.1 Data Collection

We conducted ten semi-structured interviews with eleven AI startup founders in the DACH region between January and February 2024. By engaging these founders as "knowledgeable agents" (Gioia et al., 2013, p. 17), we captured their unique experiences and perspectives, with the semi-structured format allowing for the flexibility needed to gather rich, detailed insights. The interviews covered the following thematic areas (1) role description, (2) startup development and founding history, (3) organizational goals and motivations, (4) task allocation and role distribution, (5) product description, (6) AI challenges, and (7) future plans. After these ten interviews, thematic saturation (Glaser & Strauss, 1967) was reached, as no new insights emerged, indicating that further interviews would not contribute additional value to the data set. The interviews provided a profound introduction to the domain while highlighting specific nuances (Eisenhardt & Graebner, 2007).

Interview participants were selected based on their roles as founders or co-founders of AI-integrated startups, ensuring diversity across industries to gather universally applicable insights. Participants were recruited through various AI-focused incubators, accelerator programs, and networks, with initial contact made via email and LinkedIn. The interviews were conducted virtually, lasting an average of 29 minutes. Nine interviews were held with individual founders, while one interview included two co-founders (B1 and B2). Throughout the process of interview execution and analysis, ensuring the validity and reliability of the acquired data, as well as adhering to ethical standards was prioritized. Any discrepancies in coding were addressed and resolved through a consensus-based approach and discussions by the two authors to ensure a cohesive interpretation. The computer-assisted qualitative data analysis software MAXQDA was utilized as a tool to facilitate the coding and clustering procedure. Table 2 summarizes participant demographics.

Table 2. Overview of interview partners

ID	Role*	Founding Year	Team Size	HQ	Target Industry
A	CSO	2022**	9	Osnabrück	Agri/FoodTech
B1	n/a	2023	6	Munich	Green & Materials Tech
B2	Product Development	2023	6	Munich	Green & Materials Tech
C	Managing Director	2022**	5	Hamburg	Green & Materials Tech
D	Managing Director	2023	7	Munich	Health & Human Sciences
E	COO	2022**	9	Zurich	Enterprise & Infrastructure
F	IT Solutions Provider	2023**	5	Munich	IT & Digital Services
G	n/a	2023	2	Munich	IT & Digital Services

H	n/a	2018**	35	Munich	Health & Human Sciences
I	n/a***	2023**	1	Munich / Heilbronn	IT & Digital Services
J	Co-CEO	2023**	2	Berlin	Agri/FoodTech
** indicates the thematic focus of startup co-founder – if "n/a" = co-founder without specific focus; ** indicates that startup is already incorporated; *** I is a solo-founder*					

3.2 Data Analysis

After transcribing the interviews, we analyzed the data iteratively using the systematic coding framework by Strauss and Corbin (1990). First, we applied open coding to organize the data and identify key issues and topics, resulting in the development of 362 new codes due to the novelty of the subject matter. In the next stage, axial coding (see Table 3 for an example), we consolidated these open codes, facilitating theme identification and confirming the relevance of specific sections to our research question. Finally, we condensed the axial codes into selective codes, allowing us to identify overarching concepts and patterns across the dataset. Figure 1 depicts an exemplary flow chart of the coding procedure.

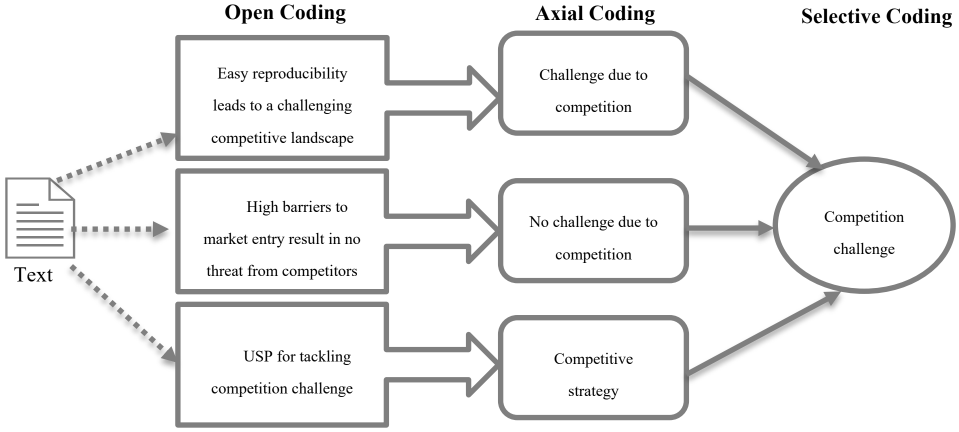

Figure 1. Exemplary flow chart of coding procedure

Table 3. Exemplary coding

Open Code	Illustrative Data
Benefits of AI as a buzzword in investor talks	Investors are really interested to talk with us because they see that the market and AI is really interesting. I see benefits in the buzzword of AI. (D)
Challenge due to costly AI architecture	It's just too expensive even if you use the 3.5 models it's just too expensive. (I)

4 Findings

The following analysis categorizes challenges described by the interviewees. Later the discussion section explores mitigation strategies grounded in effectuation principles, such as leveraging existing resources and embracing uncertainty (Sarasvathy, 2001).

Resources Challenge

AI startups consistently reported challenges in securing core resources such as high-quality data, AI models, and skilled technical staff. These resources are essential not only for product development but also for achieving long-term scalability.

Access to relevant data emerged as a major obstacle. One founder emphasized its value directly: *"It's hard because it [the data] costs that much money and data is usually also the money"* (F). Startups in data-intensive fields noted that collecting, cleaning, and structuring large volumes of training data requires significant time and effort. One interviewee identifies the decision regarding AI infrastructure and model as a primary challenge, as they state: *"The biggest challenge of building models is they are resource intensive, and you need to collect a lot of datasets"* (J). To reduce costs, many founders turned to publicly available sources. For example, founders mentioned using open-access ground truth data (A), government datasets (E), and empirical sources already available in their domains (H). In some cases, startups formed partnerships with early customers to gain access to proprietary data. As one founder explained: *"We work with […] [name of partner] and their facilities, […] we collect the data, […] we take some of the data and we use it to predict some estimates and give them back"* (J).

Similarly, the cost and complexity of building AI models were identified as barriers – especially for startups with limited funding. Several founders noted that commercial AI services from companies like OpenAI or Microsoft were too expensive, even after they began generating revenue. One interviewee explains that the use of an external model remains excessively expensive even after generating revenue (I). Many opted to start with open-source APIs or low-cost MVPs. These solutions were often customized over time. One founder described their lean launch: "*We immediately did something with AI, but something super simple. Basically, we developed a questionnaire, […] put it into an LLM, […] made text out of it and showed this to the […] [partner name]. And they were fascinated how quickly we came up with something that worked"* (D). Across the interviews, this kind of early, low-cost experimentation was common.

Human capital – especially hiring or attracting a capable Chief Technology Officer (CTO) – was also highlighted as a pressing challenge. One co-founder described this bluntly: *"I think right now our biggest challenge is to find a CTO"* (B2). Interviewees pointed to a lack of qualified AI engineers, the need for shared entrepreneurial vision, and strong competition from established companies offering better compensation packages. Some reported that initial hires came through existing networks. One founder explained: *"Luckily, there's a good connection to the […] [university environment] still. And there was a lot of referrals, word of mouth. I think this helped us at the beginning to get the right people on board"* (H).

Competition Challenge

Startups varied in their perception of competition. Some founders believed their market was large enough to support many players, and their offerings were distinct enough to avoid direct competition (J, H). Others, particularly those building general-purpose AI solutions, felt pressure from both emerging teams and larger incumbents.

Several founders mentioned that the use of public datasets and open-source models increased the risk of their ideas being copied. One explained: *"So, teams who are going after a generalist type of solution obviously are put in the same bucket […] [with] bigger organization or better-founded teams"* (G). Furthermore, there are many fast-moving teams innovating in the AI space, sometimes better founded (G,) or established companies developing their own spin-offs (C). Some believe that the market was either too vast (J) or the approaches to problem-solving differed (H). Hence, the perception of competition highly depends on industry dynamics, market structures, size, and product offerings.

To differentiate, some startups leaned heavily on customer-specific tailoring and deep domain relationships. Founders described working closely with partners to shape their products and reduce switching costs (G, H). Personal networks and being early in the market were perceived as competitive advantages (C, D).

Regulation Challenge

Perceptions of regulation varied widely. Some startups expressed frustration with uncertainty around the GDPR and EU AI Act. One founder called these frameworks just an *"extra concern, […] extra cost and an extra threat for companies"* (I). Another described navigating privacy rules as *"a forest"* they eventually worked through, only to face new compliance demands (D).

Conversely, other founders believed regulation offered a long-term advantage. Some said that having data privacy processes in place made their company more appealing to enterprise customers. As one explained: ""*"good thing [that] you [the startup] are [is] from Germany, Europe, […] [since] there is a lot of data security [and] bureaucratic burdens [in Germany], that could be [an] advantage because they [, foreign customers] also, of course, care how data is being treated"* (H). Further he added that rules could deter less-prepared competitors and raise the barrier to entry (H).

To manage compliance, several startups relied on legal support or participated in policy-focused workshops (F, E). Others simplified their data structures or anonymized datasets to reduce exposure.

Uncertainty Challenge

The degree of uncertainty startups faced varied depending on founder experience, startup maturity, and the complexity of the AI being developed. Founders with prior experience or simpler AI use cases reported lower levels of uncertainty (A, D). In contrast, first-time founders and those exploring complex models described frequent unpredictability (J, B1).

Many addressed this challenge through iterative experimentation and by working closely with users. One founder shared that they tested features quickly and refined them based on feedback (B1). Another stressed the importance of adapting over time

(C). Most startups also emphasized the value of having a strong support network. As E stated: *"The network is everything. The network is beyond"*.

Across interviews, uncertainty was not necessarily viewed as negative, but rather as something to be navigated with flexibility and connection.

5 Discussion

5.1 Linking Empirical Challenges to Effectuation Theory

The challenges and mitigation strategies varied among the startups in terms of type and severity. The interview partners primarily indicate that they do not perceive a significant difference from traditional IT startups but instead viewed the integration of AI as an enhancement, enriching the value proposition for the customer and the startup itself. This corresponds to the literature, suggesting that AI has the potential to enhance existing customer value by, inter alia, automating repetitive tasks and entire processes and analyzing vast unstructured data, thereby reducing costs (Garbuio & Lin, 2019). Further, the AI models are often capable of consistently improving themselves without human supervision (Weber et al., 2022) and Schulte-Althoff et al. (2021) highlight that AI startups are more flexible in terms of product adaption and profit from the learning capabilities inherent in AI technology. Consequently, the interviewees agree with the literature, outlining benefits for the customer and the AI startup itself.

The interviewees acknowledge certain challenges resulting from the integration of AI, including resource challenges, competition-related challenges, challenges due to regulation and uncertainties. However, the opinions regarding the severity of the challenges among the interviewees vary. Scholars name comparable challenges (Schulte-Althoff et al., 2021), nevertheless, there is a lack of in-depth analysis regarding the unique challenges specifically faced by AI startups.

The challenges AI startups face – from resource acquisition (e.g., data or talent), regulation, and uncertainty – are in general shaped by high dynamism and constrained resources. Effectuation theory provides a relevant framework, emphasizing entrepreneurial action based on available means, partnerships, affordable loss, and adaptation to contingencies (see Table 4 for an overview). In this section, we also connect the findings to prior research on AI entrepreneurship and digital innovation.

Table 4. Overview on challenges and corresponding effectuation principles

Challenge		Effectuation Principle	Empircal Strategy	Supporting Literature
Resources	Data Access	Bird-in-Hand, Crazy Quilt	Use of customer data, open datasets, and network-based sourcing	Bessen et al. (2022), Weber et al. (2022)
	AI Model Costs	Affordable Loss, Bird-in-Hand	Use of open-source APIs, building simple MVPs	May et al. (2020), Zahra (2021)
	Talent Acquisition	Bird-in-Hand, Crazy Quilt	Hiring through university networks, informal referrals	Fatima et al. (2021), Berg (2023)

Competition	Crazy Quilt	Co-develop with customers, build USPs from personalization	Bessen et al. (2022), McDonald & Eisenhardt (2020)
Regulation	Lemonade, Crazy Quilt	Legal partnerships, compliance as brand differentiator	Åström et al. (2022), Bessen et al. (2022)
Uncertainty	Affordable Loss, Crazy Quilt	Rapid testing, iteration, relying on mentor and peer networks	McMullen & Shepherd (2006), Yrjönkoski & Suominen (2018)

Startups faced barriers in acquiring quality data and building or accessing advanced AI models. Many founders used open-access datasets or partnered with customers to access proprietary data. These practices align with Bessen et al. (2022), who describe data partnerships as a competitive advantage, and Weber et al. (2022), who note that AI startups often rely on external or customer-provided data.

To cope with costly model development, founders adopted open-source APIs and MVPs – a strategy consistent with Sarasvathy's affordable loss principle. May et al. (2020) and Zahra (2021) highlight similar bootstrapping approaches in early-stage digital ventures.

Hiring technical talent was a recurring concern, especially for early-stage AI ventures. Founders often relied on existing university networks, informal referrals, and training junior developers internally. This approach reflects the bird-in-hand principle and mirrors the findings of Fatima et al. (2021) and Berg (2023), who underline the scarcity and high cost of AI talent.

Perceptions of competition varied, depending on product complexity and market maturity. Some startups built USPs by customizing their solutions for clients or using proprietary data, which aligns with McDonald and Eisenhardt's (2020) view on competitive distinctiveness. The use of partnerships and network ties for customer acquisition supports Sarasvathy's crazy quilt principle.

The interviews revealed mixed perceptions of regulation: some viewed it as a burden, while others turned it into a strategic asset. This divergence aligns with Bessen et al. (2022), who note that regulations can both constrain and create opportunities. Startups that framed compliance as a trust-building tool exemplify the effectuation principle of lemonade.

Uncertainty was seen as more manageable by experienced founders or those working with simpler models. Most startups emphasized iterative testing and peer networks as tools for navigating ambiguity. These findings resonate with McMullen and Shepherd's (2006) view that uncertainty is subjectively perceived and with Sarasvathy's view that action can precede prediction. The importance of networks echoes Yrjönkoski and Suominen (2018), who argue that effectuation is particularly useful in digital entrepreneurship.

Synthesis

Across all challenges, effectuation theory provided useful heuristics for decision-making in uncertain, resource-constrained environments. Strategic partnerships, experimentation with low-cost solutions, and iterative customer feedback loops were common coping mechanisms. The findings suggest that nascent AI startups succeed not by reducing uncertainty, but by embracing it through collaborative and adaptive action.

This study contributes to the literature on digital entrepreneurship by conceptually and empirically distinguishing AI startups from traditional digital ventures and by exploring how effectuation theory applies in this novel context. While effectuation has been widely used to understand early-stage decision-making under uncertainty, its application to AI entrepreneurship – where uncertainty stems from algorithmic complexity, regulatory flux, and data dependencies – remains limited. Our findings suggest that AI-specific factors (e.g., reliance on external platforms, high iteration cycles, and regulatory learning) influence how founders enact effectual logic, particularly regarding the principles of affordable loss, crazy quilt, and pilot-in-the-plane.

By mapping domain-specific challenges to effectuation principles, we refine the understanding of how effectuation unfolds in environments shaped by technological opacity and institutional emergence. This offers a theoretical extension of effectuation by identifying context-sensitive enactments of its core principles in highly dynamic, AI-driven markets.

The findings offer actionable insights for AI startup founders, investors, and policymakers. For founders, the study highlights effectual strategies such as forming early-stage data partnerships (bird-in-hand, crazy quilt), leveraging open-source tools to manage costs (affordable loss), and iterating with minimal viable models under regulatory constraints (lemonade). These heuristics can support more resilient decision-making in high-uncertainty environments. For investors, understanding how AI founders respond to uncertainty through effectuation can inform investment criteria and support strategies – especially in evaluating founding teams' adaptability and network leverage. Finally, for policymakers, the results underscore the need for AI-specific regulatory clarity and the value of regulatory sandboxes to support experimentation. Encouraging partnerships between startups and institutions (e.g., hospitals, universities) can also help overcome data access barriers and facilitate responsible innovation.

5.2 Limitations and Future Research

While this study focuses on AI startups, the insights drawn from these nascent ventures offer valuable lessons for established organizations undergoing digital transformation. For example, established firms might benefit from adopting agile, low-cost prototypes to pilot AI-driven solutions or by forming partnerships with emerging AI startups to supplement their digital transformation strategies. This cross-application of startup strategies could enable traditional firms to embrace a more iterative, resource-efficient approach, aligning their transformation processes with the rapid pace of digital innovation.

The interview participants were recruited from a network connected to the startup ecosystem of a technical university in southern Germany, which may introduce minor biases. However, the startups were selected randomly with the sole condition of offering a product involving AI integration, supporting the internal validity of the findings. The small sample size, along with the reliance on self-reported data, may further limit generalizability, as participants might portray their experiences favourably. The initial objective to interview AI startups targeting varied industries, offering distinct products, and positioned at different development stages was achieved. This diversity enriched the exploratory aims of the study, though it also presented challenges in comparing findings, thereby limiting external validity. While this study offers rich insights into AI startup challenges and effectuation-based strategies, it also opens avenues for further investigation. Future research may focus on specific industries, product types, levels of AI integration, or development stages to enhance contextual depth. Additionally, comparative studies across geographic regions – both within Germany (e.g., Berlin, Hamburg, Rhine-Ruhr) and internationally (e.g., US vs. European startups) – could shed light on how regulatory frameworks, funding landscapes, and access to talent influence entrepreneurial decision-making. Quantitative studies incorporating metrics such as time-to-market, stakeholder engagement, and resource utilization efficiency would also complement our qualitative findings and offer broader generalizability. Collectively, these directions underscore the need for more granular and comparative research on AI entrepreneurship in dynamic environments.

6 Conclusion

AI startups are currently a prominent topic, marked by a significant increase in investments in this sector and media coverage. Given the significant level of prevailing uncertainty in the environment, particularly for nascent ventures, it is essential to offer academic guidance for founders.

This study aimed to assess the applicability of effectuation theory in navigating the distinctive challenges AI startups face. Through qualitative interviews with founders and a complementing literature analysis, a framework has been proposed to help founders address these challenges. AI integration introduces both advantages and specific challenges, such as data acquisition, model development, and talent sourcing. Additionally, competition, regulatory hurdles, and uncertainty present significant obstacles, which vary depending on factors like the startup's maturity, industry, product, and founder experience.

However, effectuation principles, particularly crazy quilt and affordable loss, offer promising strategies for mitigating these challenges. Making use of effectuation principles provides AI startups founders with flexible tools to advance their ventures based on available resources and their startup's unique needs.

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