Stockholm School of Economics
1351 Master’s thesis in Business Management
Academic year 2025–2026

Effectuation in the Age of AI: How Founders of AI-Based Startups Navigate Product Decisions

Ella Appelholm (42818) and Sara Boras (42782)

Effectuation theory, which describes how entrepreneurs make decisions under uncertainty, emerged from studying expert entrepreneurs navigating that uncertainty (Sarasvathy, 2001). However, AI-based software startups present a fundamentally transformed entrepreneurial context, where relative capital abundance, younger and less experienced founders, and a paradoxical uncertainty where generative AI tools simultaneously expand possibilities while potentially enhancing predictive capabilities. This thesis examines how founders of AI-based software startups apply decision logics in software product development decisions, through the lens of effectuation theory. Through semi-structured interviews with 17 early-stage AI startup founders in Sweden, we find that effectual decision logic persists despite transformed antecedent conditions but manifests in reconfigured ways. First, affordable-loss logic shifts from financial to temporal currency, as capital abundance and AI-reduced experimentation costs make time the scarcest resource. Second, AI tools lower experience thresholds for effectual decision-making by augmenting founders' means. Third, AI tools transform uncertainty structure, heightening isotropic uncertainty from expanded possibilities while reducing effect uncertainty through development acceleration. Founders demonstrate all of Sarasvathy's original effectuation principles: means-driven logic, affordable loss, leveraging contingencies, pre-commitments, and control as the unifying effectuation principle. These findings place AI-based startups as a domain that reshapes, but ultimately enables, effectual logic. Finally, this study points toward several avenues for future research on how AI transforms entrepreneurial decision-making across contexts.

Keywords: Effectuation, AI Startups, Entrepreneurial Decision-Making, Product Development, Uncertainty

Supervisor:	Mickaël Buffart
Date examined:	17th December 2025
Discussant(s):	Jannis Heidemann and Anna List
Examiners:	Hans Kjellberg and Örjan Sjöberg

Acknowledgements

We want to express our sincere gratitude to our supervisor, Mickaël Buffart, Assistant Professor in Entrepreneurship at the House of Innovation of the Stockholm School of Economics, for his kindness, smiles, guidance and support in this project. Further, we wish to thank Professor Susanne Sweet and Professor Karl Wenneberg for guiding us through the thesis writing process with their seminars and knowledge.

We also want to say thank you to all the founders who took time out of their busy schedules to share their personal experiences with us during the interviews. Additionally, we would like to thank our friends at Founders House, who provided valuable insights, inspiration and support – you continue to amaze us every day. Lastly, we would like to express our gratitude to our beloved friends and family who have supported us through this journey.

Once again, thank you.

Sara and Ella

Table of Contents

1. Introduction

1.1 Background and Problem Formulation

During her doctoral thesis in the 1990s, Sarasvathy sat down with 27 *expert* entrepreneurs, each averaging 15 years of experience, to explore how they make decisions under uncertainty (Foss et al., 2023). This was the start of effectuation theory (Sarasvathy, 2001), which went on to become one of entrepreneurship literature's most influential frameworks (Fisher, 2012; Gregoire and Cherchem, 2020; Frese & Gielnik, 2023). The theory describes a decision-making logic fundamentally different from traditional causal decision logic, which follows the logic "to the extent we can predict the future, we can control it" (Sarasvathy, 2001, p. 252) and emphasizes goal-driven processes. Effectuation follows the inverse logic "to the extent we can control the future, we do not need to predict it" (Sarasvathy, 2001, p. 252). Empirical evidence demonstrates that effectuation and causation are complementary approaches (Smolka et al., 2018; Koller et al., 2022), and that high uncertainty and resource scarcity drive effectual logic in contexts involving experienced entrepreneurs (Dew et al., 2009a; Jiang & Tornikoski, 2019; Koller et al., 2022; Reymen et al., 2015; Fisher, 2012).

However, a new entrepreneurial context has emerged that challenges these previously identified antecedents of effectual logic, AI-based startups, i.e., ventures that develop artificial intelligence (AI) solutions as their core product offering (Vásquez et al., 2026). In 2024 alone, more than 2,000 AI companies received funding, and this number has grown steadily in recent years (Stanford HAI, 2025), underscoring the growing importance of this context for entrepreneurship research. These entrepreneurs operate under conditions that differ fundamentally from those in which effectuation has typically been studied. We identify key differences at two levels: the environment in which founders operate and the characteristics of the decision makers themselves.

Firstly, from the perspective of the venture capital (VC) landscape, AI-based startups have attracted an increasingly more capital, with European investment projected to reach $44 billion in 2025, where 18 percent of 2024 investment went to AI-based startups (Dealroom, 2024; State of European Tech 2025, 2025). Globally, AI investment reached $131.5 billion in 2024, representing 35.7 percent of all venture funding (Robbins, 2025), and adjusted for population, Sweden ranked the highest in private investment in AI (HAI Stanford, 2025). This contrasts with the resource scarcity that has traditionally characterized early-stage ventures, and the conditions under which previous research has been conducted (Sarasvathy, 2001; Fisher, 2012). Moreover, the founders themselves have changed. At the world famous incubator Y Combinator, the median founder age fell from 30 in 2022 to 24 in 2024-2025, with accepted applicants aged 18-22 increasing by 110% year-over-year (Weiss, 2025). Similarly, a report by early-stage VC firm Leonis Capital finds that AI startup founders are now typically 26-27 at founding (Leonis Capital, 2025). Consequently, these younger founders potentially lack the extensive entrepreneurial experience that Sarasvathy's (2001) original research identified as central to effectual decision-making, a pattern that was confirmed in our sample. Moreover, the technological capabilities available to founders have fundamentally shifted, where generative AI (GenAI) and large language models (LLMs) have compressed development timelines by 25 to 55 percent though AI coding assistants, while maintaining comparable code quality (Peng et al., 2023). These tools enable founders with limited programming experience to build products (Obschonka et al., 2024), lowering barriers that previously required years of accumulated technical expertise.

The uncertainty landscape presents an interesting paradox. On one hand, AI as a general-purpose technology evolves at an accelerating pace (United Nations, 2025; Yee et al., 2025), and AI ventures are distinguished by "exponential growth and high potential for creative destruction" (Gofman and Jin, 2024, p. 631), making future market states increasingly difficult to predict. Furthermore, GenAI tools dramatically expand what founders can build, creating an increase of possible ideas and product directions (Ramoglou et al., 2025; Townsend & Hunt, 2019). Founders face not too little information but too many possibilities. On the other hand, AI simultaneously has shown to offer enhanced predictive and validation capabilities, enabling more prediction-based planning (Raneri et al., 2023). The aggregate impact of AI on perceived uncertainty and entrepreneurs' decision-making remains unclear. The described context matters because it challenges the foundational conditions under which effectuation theory was developed (Sarasvathy, 2001). Effectuation emerged from studying expert entrepreneurs facing high uncertainty (Sarasvathy, 2001). Resource scarcity, accumulated experience, and uncertainty have been empirically identified as key drivers of effectual logic (Fisher, 2012; Frese et al., 2020; Harms & Schiele, 2012; Jiang & Tornikoski, 2019; Read et al., 2009a). Yet AI-based startups operate under nearly inverse conditions with financial abundance, limited founder experience, and paradoxical uncertainty, where AI tools may both expand decision complexity and enhance predictive capabilities.

This puzzle is examined through product development decisions, specifically how founders determine which features to build, prioritize, include, or exclude. Product development represents a core decision domain for early-stage software startups (González et al., 2024), where founders strongly influence decisions particularly when formal processes are limited (Melegati et al., 2019).

Specifically, we ask: *How do AI-based startup founders apply effectual decision-making logic in product development decisions, and how do AI development tools influence these decision processes?*

Through 17 semi-structured interviews with Swedish early-stage AI-based software startup founders, we examine which decision-making logics they employ in feature prioritization.

1.2 Research Purpose and Relevance

1.2.1 Academic Relevance

This study contributes to entrepreneurship and software startup research by examining how effectuation operates in AI-based ventures where rapid prototyping, relaxed constraints, and comparatively inexperienced founders reshape conditions traditionally associated with effectual logic. Software startup scholars call for work that explains real decision-making rather than prescribing ideal methods (Bajwa et al., 2016; Nguyen-Duc et al., 2021; Pantiuchina, 2017; Ralph, 2016; Unterkalmsteiner et al., 2016). Effectuation theory has been critiqued for limited empirical testing and in need of further refinement (Arend et al., 2015; Edmondson & McManus, 2007; Perry et al., 2012), with empirical work focused mainly on professionally experienced individuals (Dew, et al., 2009a; Galkina et al., 2022; Sarasvathy, 2001; Wiltbank et al., 2006) and only limited attention to less experienced founders (e.g., Park et al., 2025). Addressing these gaps, this study adds empirical insights to software entrepreneurship and to effectuation theory under a changed context, particularly regarding the experience antecedent. As AI tools are central to the entrepreneurs' decision-making, it also responds to calls for research on AI tools' impact on perceived uncertainty and the democratization of entrepreneurship (Obschonka et al., 2024). By examining product development decisions in AI-based companies, this study both extends understanding of decision-making in AI ventures and observes effectual logic in practice, contributing to its theoretical refinement.

1.2.2 Practical Relevance

This study provides knowledge about how AI-based startup founders make product development decisions under conditions of AI-supported development and compressed timelines. For founders, the study makes visible decision-making patterns of their peers, possibly giving them a frame for reflection of their own decision-making process. If entrepreneurs and educators aim to use effectuation purposefully, this can also give insights into how this might come about in contexts of less entrepreneurial experience. For investors and startup support organizations, the research provides insight into how AI-focused founders operate in resource environments that differ from traditional startups.

The relevance of this study appears particularly high given current industry discourse around a potential "AI bubble" (i.e. a tech bubble which is created by unsustainable growth, due to speculation, that often end up in a crash (Floridi, 2024)) (Allyn, 2025; Brandom, 2025; Islam and Clun, 2025; Kost, 2025). AI startup valuations have doubled or tripled within months (Garfinkle, 2025), yet concerns about sustainability have emerged, with observers introducing terms like "vibe revenue" to describe startups backed by hype (i.e.,“a collective vision and promise of a possible future, around which attention, excitement, and expectations increase over time” (Logue and Grimes, 2022, p. 1055)) rather than sales (Considine and Kharpal, 2025). Understanding how founders, identified as an important variable for startup success (Aryadita et al. 2023), make product development decisions may reveal the underlying logics shaping this rapidly evolving entrepreneurial domain. While this study does not evaluate which decision-making approach leads to superior outcomes, examining whether founders employ effectual or causal logics contributes to understanding the cognitive foundations of AI entrepreneurship at a critical juncture. Such insight may inform future research on how different decision-making logics lead to success in AI ventures.

1.3 Research Question

Building on the gap between traditional effectuation literature, which has largely assumed and been evaluated in contexts of high uncertainty, experienced entrepreneurs, and resource-scarce contexts, and the reality faced by AI-based software startup founders, this study examines how established decision-making frameworks operate in an AI-shaped landscape. This leads to the central research question:

How do AI-based startup founders apply effectual decision-making logic in product development decisions, and how do AI development tools influence these decision processes?

1.4 Delimitations and Scope

Geographical Scope

Focusing on Sweden is theoretically justified by the strong innovation ecosystem and its concentration of AI investment. Sweden ranks fourth globally in both the Global Innovation Index (WIPO, 2025) and private AI investment ($4.34 billion in 2024; Stanford HAI, 2025). This context offers a setting where founders operate with comparatively abundant access to resources, enabling examination of decision-making in conditions of selective abundance rather than absolute scarcity.

Temporal Scope

The temporal delimitation to 2025 captures a distinctive moment in entrepreneurial history characterized by widespread access to sophisticated AI development tools, particularly large language models and AI-powered code generation capabilities (Peng et al., 2023; Dell'Acqua et al., 2023; Batista et al., 2024). This period represents the first cohort of founders who have conducted the majority of their product development with GenAI assistance from inception, distinguishing their cognitive processes and decision-making contexts.

Demographic & Unit of Analysis: the Founder

The study examines the individual founder as the unit of analysis, reflecting research that identifies founders as the primary locus of strategic decision-making in early-stage ventures (Baron, 2004; Mitchell et al., 2002) and aligning with effectuation theory's focus on individual-level heuristics and cognition (Sarasvathy, 2001). The study focuses on young founders, sub-32 years old with an average age of 24 (aligning with Forbes (2005) and Politis et al., (2010)), mirroring the current AI entrepreneurship landscape where founder demographics have shifted younger (Weiss, 2025), indicating a cohort whose professional development occurred during the AI revolution. Furthermore, these founders are found to typically have limited prior entrepreneurial experience. We use the terms founder and entrepreneur interchangeably throughout this paper.

Venture Stage, Type and Decision Area

We look at the specific decision domain of product development (e.g., determining which features to build, what to include or exclude, and how to prioritize between them). Product development is central for software startups, as they are typically built around a single product, tightly coupling business and software engineering decisions (Paternoster et al, 2014; Berg et al. 2018). This study examines early-stage ventures (interchangeably referred to as startups), defined as pre-seed or seed stage (De Clercq et al., 2006), where product definition, which includes new product development as well as the technical parts, is recognized as critical (González et al., 2024) and where effectual logic is theoretically most prevalent (Sarasvathy, 2001; Frese et al., 2020). The sample consists exclusively of early-stage AI-based software startups, defined as ventures whose core value proposition is fundamentally enabled by GenAI technologies. The delimitation excludes ventures where AI is peripheral, as well as AI infrastructure, hardware, or consulting firms.

1.5 Structure of the Thesis

The remainder of the thesis develops the theoretical foundation of effectuation theory, and recent studies in the field. Further, it describes the methodological approach, before presenting the empirical findings together with their analysis and discussion. The thesis concludes with key implications, limitations, and directions for future research.

2. Literature Review & Theoretical Framework

This section begins by outlining the foundations of effectuation theory and its core principles as introduced by Sarasvathy (2001). It then reviews research on the antecedents of effectual decision-making through both foundational and recent literature. Before ending with a summary of the previous research.

2.1 Entrepreneurial Decision-Making Under Uncertainty

Knight's (1922) work on entrepreneurial decision-making under uncertainty has fundamentally shaped modern entrepreneurship theory (Sarasvathy, 2001; McMullen & Shepherd, 2006; Alvarez & Barney, 2005; Townsend et al., 2018). Knightian uncertainty, where environments shift in unpredictable ways, compels entrepreneurs to make complex decisions based on limited and often ambiguous information (Knight, 1922; McMullen & Shepherd, 2006; Packard et al., 2017). Decision-making can be understood as selecting among alternatives and their potential consequences (Packard et al., 2017), which is shaped by a decision logic, i.e., the beliefs and assumptions through which individuals make sense of situations and determine how to act (March & Olsen, 1975; Simon, 1959). A key point of distinction is whether this decision logic relies on prediction or on control (Wiltbank et al., 2006; Sarasvathy, 2001), where prediction-oriented approaches treat the future as something that can be anticipated through analysis (Ansoff, 1965; Porter, 1985), whereas control-oriented approaches view the future as something enacted through action (Weick, 1979; Sarasvathy, 2001).

2.2 Effectuation Theory

2.2.1 The Foundational Framework

In decision-making, experienced entrepreneurs make decisions in ways that diverge from traditional management assumptions (Sarasvathy, 2001). Sarasvathy (2001) introduced effectuation as a set of principles that expert entrepreneurs apply to enable control of the future, which is inherently unpredictable, shifting attention away from assumed economic outcomes and toward how context and available options shape entrepreneurial choices in the moment. Sarasvathy (2001) referred to these as 'principles', but are also referred to as 'logical frames' (Dew et al., 2009a), 'behavioral principles' (Perry et al., 2012), and decision-making 'heuristics' (Werhahn et al., 2015). Regardless, effectuation has emerged as one of the most frequently cited theories within the entrepreneurship field since Sarasvathy's first article in 2001 (Dias et al., 2019).

Effectuation and causation is contrasted in previous research, to distinguish between effectuation and traditional business planning (Brettel et al., 2012; Sarasvathy, 2001). Causation follows the logic of "*to the extent we can predict the future, we can control it*" (Sarasvathy, 2001, p. 252), emphasizing goal-driven processes where entrepreneurs start with predetermined objectives and acquire necessary means. Effectuation follows the inverse logic "*to the extent we can control the future, we do not need to predict it*" (Sarasvathy, 2001, p. 252), describing a means-driven process where entrepreneurs start with available resources and select among possible goals. Sarasvathy (2024) later clarified that the means-driven bird-in-hand principle represents only one of effectuations five principles, which are all reliant on the aspect of control, and moving away from the need to predict. Conversely, causation places great emphasis on prediction but little emphasis on control (Karami et al., 2020; Perry et al., 2012; Wiltbank et al., 2009). Put differently, an action is not effectual solely because it stems from means rather than goals, but because it minimizes the need for being predictive (Sarasvathy, 2024). Although entrepreneurs may personally favor one decision logic over the other, which logic dominates depends on how they perceive the environment (Perry et al., 2012; Reymen et al., 2015; Sarasvathy, 2022).

Inspired by the prior literature on the effectual logic employed by expert entrepreneurs in decision-making, this study views effectuation and causation as different decision-making logics (Sarasvathy, 2001; Dew et al., 2009a; Frese et al., 2020). Empirical studies show that effectuation and causation are not mutually exclusive opposites but dynamically intertwined and complementary (Koller et al., 2022; Smolka et al., 2018; Matalamäki, 2017), they rarely, if ever, occur in pure forms (Rapp, 2022), a point also made by Sarasvathy (2001).

2.2.2 The Principles of Effectuation

Since Sarasvathy (2001) first introduced her five principles of effectuation, scholars have labeled and grouped them in different ways. Some studies retain five principles (Dew et al., 2009a; Werhahn, 2015), while others condense them into four dimensions for empirical measurement (Chandler et al., 2011; Brettel et al., 2012). Chandler et al. (2011) add an explicit dimension of *experimentation*, arguing that effectuators try out different approaches before committing to a particular concept, an idea grounded in Sarasvathy's (2001) discussion of market-based trial-and-error. Although the number and labels vary, these interpretations all build on Sarasvathy's foundational concepts.

Sarasvathy (2001) highlights control, rather than prediction as the central, unifying principle of effectuation, expressed as the '*Pilot-in-the-Plane'* principle. Effectual entrepreneurs separate their environment into what they can and cannot influence and then concentrate their efforts on the controllable aspects in order to shape the environment (Sarasvathy et al., 2008). This view assumes that the environment is not fixed but can be created or co-created through entrepreneurial action. As Sarasvathy (2024) explains, effectuators use the resources already under their control to help bring about new and unpredictable future. Thus, in effectuation, control is not just a result of action, it is the guiding strategy, making prediction largely unnecessary (Sarasvathy, 2024). The remaining four principles from Sarasvathy's (2001) original framework are (2) means-driven action (*Bird-in-Hand*), (3) affordable loss, (4) stakeholder pre-commitments (*Crazy Quilt*), and (5) leveraging contingencies (*Lemonade*). This study focuses primarily on these four principles as a primary lens for analysis, following Read et al. (2009b), who describe effectuation as entrepreneurs using *means*, *affordable loss*, *stakeholder relationships*, and *contingencies* to create and develop new opportunities. The terms stakeholder relationships and pre-commitments are used interchangeably throughout this paper.

Means-driven

Also known as *Bird-in-hand* (Sarasvathy, 2001) highlights beginning from existing resources rather than forecasting future conditions. Effectual entrepreneurs rely on "who they are, what they know, and whom they know" (Sarasvathy, 2001, p. 249) to envision and construct potential opportunities (Sarasvathy, 2001). Whereas causal logic seeks to predict future needs and then obtain the necessary resources, effectuation centers on acting with what is already under one's control (Grégoire & Cherchem, 2020; Prashantham et al., 2019).

Affordable loss

This principle explains how entrepreneurs limit their commitments to what they can afford to lose rather than investing based on expected returns. Effectual decision-makers assess the possible downside and choose actions where the worst-case loss remains acceptable

(Sarasvathy, 2001). In contrast, a causal logic would estimate future returns and invest to maximize potential upside (Sarasvathy, 2001; Read et al., 2009b).

Stakeholder relationships

Stakeholder pre-commitments, articulated in Sarasvathy's (2001) "crazy quilt" principle, underscore the central role of partnerships in effectuation. Entrepreneurs engage with stakeholders such as customers, suppliers, and community members who voluntarily commit resources and help co-create opportunities. These self-selected partners broaden the resource base and enable a more control-oriented strategy than one grounded primarily in market research or competitive analysis (Sarasvathy, 2001; Wiltbank et al., 2006). In contrast, a causal approach typically involves stakeholders only after a clear business plan has been defined and tends to see them mainly through a competitive, market-driven lens (Perry et al., 2012).

Contingencies

This principle emphasizes staying flexible and treating unexpected events as opportunities for learning and action (Sarasvathy, 2001). Firms frequently face surprises or breaks in continuity that cannot be fully anticipated, particularly in uncertain environments (Hitt et al., 1998). Effectual entrepreneurs see these contingencies, whether positive or negative, as raw material for creating new ventures or markets (Sarasvathy, 2008). By contrast, a causal logic aims to minimize or avoid such surprises because they threaten the planned execution of a business strategy (Sarasvathy, 2001).

Despite its influence, effectuation theory has faced several critiques. Such as Arend et al. (2015) arguing that it lacks sufficient empirical testing, raising questions about its robustness, while others note that it underplays cultural and structural factors (Kitching & Rouse, 2020). Moreover, the use of effectual logic may overstate stakeholder trust (Goel & Karri, 2006). More recently, Rapp and Leunbach (2025) point to a positivity bias in the general effectuation literature and challenge the idea that effectuation and causation are mutually exclusive, as both logics often co-exist. Together, these critiques highlight the need to consider context and limitations when discussing effectuation.

2.3 The AI Startup Context: The Theoretical Puzzle

As discussed in the introduction, AI-based startups operate under fundamentally different conditions than the startups studied in prior effectuation research. These differences are seen as manifesting along two critical dimensions: (1) environmental characteristics, the nature of resources and uncertainty in the AI market; and (2) decision-maker characteristics, the experience and capabilities of AI startup founders. These shifts create theoretical tensions that challenge effectuation's traditional antecedents.

Effectuation theory was developed from studies of *expert* entrepreneurs facing high uncertainty (Sarasvathy, 2001). Uncertainty, experience, and resource scarcity are among the most widely discussed antecedents of effectuation (Frese et al., 2020; Fisher, 2012; Chandler et al., 2011; Dew et al., 2009a; Reymen et al., 2015; Malsch & Guieu, 2019) and were central in Sarasvathy's (2001) original paper. In the following subsections, we review how each antecedent is understood in prior research, including software and high-tech startups as comparison contexts, and then connect it to the novel context of AI-based startups, bridging effectuation theory, software engineering entrepreneurship, and AI research.

2.3.1 Uncertainty

Referring back to Sarasvathy's (2001) seminal paper, the core of effectual logic is acting in an unpredictable future, grounded in the notion of Knightian uncertainty (Knight, 1922). The use of effectuation under conditions of uncertainty has broad empirical support (Jiang & Tornikoski, 2019; Reymen et al., 2015; McMullen & Shepherd, 2006). Sarasvathy (2009) specifically discusses *isotropic uncertainty*, i.e., situations with too many possibilities, rather than too little information, as particularly enabling effectuation. When entrepreneurs are confronted with many possible paths rather than a lack of information, prediction breaks down, not because they are uninformed, but because there are simply too many plausible futures (Sarasvathy, 2009).

However, research has shown that not all uncertainty affects entrepreneurial decision-making equally. McKelvie et al. (2011) demonstrate empirically that entrepreneurs distinguish between *state uncertainty* (unpredictability of the external environment) and *effect uncertainty* (unpredictability of the consequences of one's own actions), where entrepreneurs are willing to act despite high state uncertainty but become reluctant when they cannot predict the outcomes of their own actions. Moreover, empirical evidence from software and high-tech startups, the contexts arguably most comparable to AI-based ventures, confirms uncertainty's role as a driver of effectuation while revealing how it has previously been manifested in technology-intensive environments. Software startups have traditionally been characterized by high uncertainty and rapid evolution (Kemell et al., 2023; Giardino et al., 2016) and deemed challenging (Wang et al., 2016). Frese et al. (2020) investigated antecedents of effectuation in online and high-tech startups, finding that perceived uncertainty drives experimentation and reduces causation. Meanwhile, Nguyen-Duc et al. (2021) found that effectuation logic dominated decision-making in software startups (71.4% of coded events), with MVP development, managing the costs associated with cutting corners, and customer involvement all strongly associated with effectual logic. Importantly, founders shifted between effectual and causal logics depending on the activity (Nguyen-Duc et al., 2021), providing evidence that effectuation operates as a decision logic in fast-moving, high-uncertainty technology contexts. However, these studies (e.g., Frese et al., 2020; Nguyen-Duc et al., 2021) were conducted before the widespread diffusion of LLMs. ChatGPT was released only in late 2022 (Hu, 2023), foundation models powered under 5% of natural language processing use cases in 2021 (Gartner, 2023), and McKinsey later described 2023 as the breakout year for GenAI (Chui et al., 2023). This development raises questions about whether those findings still hold in the current AI landscape.

The AI market context appears to intensify what McKelvie et al., (2011) call *state uncertainty*. AI as a general-purpose technology evolves at an accelerating pace (United Nations, 2025; Yee et al., 2025), making future market states increasingly difficult to predict (Ramoglou et al., 2025) . Moreover, GenAI tools dramatically expand what founders can build under a specific timespan (Peng et al., 2023), creating what Ramoglou et al. (2025) and Townsend and Hunt (2019) describe as an increase of possible ideas and new possibilities, a manifestation of *isotropic uncertainty*, where the human's role turns into eliminating ideas rather than generating them (Ramoglou et al., 2025). Yet, AI simultaneously promises to reduce *effect uncertainty* through enhanced predictive and validation capabilities, which would align with predictive, causal logic (Sarasvathy, 2001). Studies emphasize AI's potential to improve prediction of future states and evaluate the desirability of product decisions before full implementation (Raneri et al., 2023). Li et al. (2025) and Kim (2025) demonstrates that GenAI reduces information asymmetry especially in early-stage entrepreneurship, while Lupp (2023) shows that machine learning has a dual temporal effect, supporting effectuation principles short-term but reducing uncertainty and shifting toward causation over time. This creates a theoretical puzzle, where AI appears to simultaneously increase *state uncertainty* while decreasing *effect uncertainty*. If McKelvie et al.'s (2011) findings hold, that entrepreneurs act despite *state uncertainty* but hesitate with *effect uncertainty*, then AI tools may create particularly favorable conditions for effectual reasoning by potentially reducing *effect uncertainty*.

Moreover, Koller et al. (2022) demonstrate that decision complexity and cost interact with uncertainty to shape logic selection. They find that high-complexity, low-cost decisions (i.e., where entrepreneurs face many options and decisions are cheap), drive effectual logic through experimentation, co-creation, and means-focused reasoning. In contrast, low-complexity, high-cost decisions, that the authors call committing decisions, drive causal logic (Koller et al., 2022). Feature prioritization in AI startups appears to fit the former category, due to the AI market creating high complexity (many possible features) while simultaneously reducing decision cost (rapid, cheap prototyping). This suggests that the AI context may amplify rather than diminish the conditions under which effectuation is present.

However, Obschonka and Audretsch (2019) question whether AI will ever solve the fundamental uncertainty entrepreneurship entails, given that AI relies on learning patterns from existing data and not predicting new futures. To conclude, the overall effect of the AI market's rapid pace, ongoing technological development, and AI-tool support on *isotropic uncertainty* remains unclear, as contrasting mechanisms appear to both heighten and reduce uncertainty at the same time.

2.3.2 Experience

Early effectuation research argued that experienced entrepreneurs, with deep domain knowledge and repeated venture creation, were more likely to rely on effectual logics (Dew et al., 2009a; Read et al., 2009b; Sarasvathy, 2001). Expertise was seen as enabling effectual reasoning, where experienced entrepreneurs make faster decisions using heuristics gained through prior action, pattern recognition, leveraging networks, and navigate uncertainty more effectively than novices (Dew et al., 2009a; Engel et al., 2017; Forbes, 2005; Shepherd et al., 2015). Harms and Schiele (2012) even argued that entrepreneurial experience alone is sufficient to generate effectual action. Yet the relationship between expertise and uncertainty as revealed by McKelvie et al. (2011) suggests a more nuanced mechanism. Their finding that domain expertise moderates only *effect uncertainty,* and not *state uncertainty*, implies that experts are less discouraged by the inability to predict action outcomes, either because they genuinely embrace effectual logic or because they overestimate their predictive abilities through overconfidence.

Subsequent research has challenged the assumption that effectuation is exclusive to experts. Novice and even student entrepreneurs have been shown to employ effectual principles (Politis et al., 2010), raising doubts about whether expertise is a necessary precondition. Engel et al. (2014) demonstrate that entrepreneurial self-efficacy, which is defined as the level of confidence in the ability to perform entrepreneurial actions (Chen et al., 1998), can enable novices to use expert decision logics under uncertainty, suggesting that psychological factors may compensate for lack of experience. Moreover, Dew et al. (2009a) showed that effectuation can be learned rather than simply triggered by environmental conditions, with entrepreneurs learning through experiential trial-and-error or indirect observation of others (Minniti & Bygrave, 2001; Holcomb et al., 2009). However, experiential learning has traditionally been costly, requiring significantly more financial resources from inexperienced founders (Chandler & Hanks, 1998), and both learning modes are limited by bounded human attention, memory, and time (March, 1994; Simon, 1991).

On the other hand, the nature of experience itself may matter more than its mere presence. In Frese et al. 's (2020) investigation of experience as antecedents to effectuation in online and high-tech startups, entrepreneurial experience was shown to increase experimentation and reduce causation, while management experience favors the opposite approach. This suggests that the type of prior experience matters, entrepreneurial experience enables effectual logic while managerial experience reinforces causal planning.

Moreover, requirements engineering, i.e., understanding why and what should be built through systematic stakeholder analysis (Nuseibeh & Easterbrook, 2000), and previous research has shown that early-stage software startups do this in limited capacity, and develop products with limited user contact (Klotins, 2019). Melegati et al. (2019) found that requirements engineering becomes more feasible once these startups have secured initial customers. Requirements engineering resemble Sarasvathy’s (2001) pre-commitments with customers, and as this has been identified as a struggle for software startups, it follows that pre-commitments with customers has been difficult.

In the AI context, experience is changed with AI-based startups consisting of significantly younger founders (Weiss, 2025), and similar patterns can be seen in the broader ecosystem (e.g., the Founders House community (Founders House, 2025)). Moreover, AI coding tools enable programmers to build software products faster and more precise, arguably making it easier and thereby lowering technical barriers to entry (Batista et al., 2024; Peng et al., 2023; Dell'Acqua et al., 2023). To that point, if McKelvie et al.'s (2011) insight holds, that experts act effectually, despite *effect uncertainty,* because they can better evaluate action consequences, then AI tools that enable rapid, efficient experimentation may provide similar capabilities to novices. Moreover, Raneri et al. (2023) show that AI-based predictive models can expand what entrepreneurs learn from data by uncovering previously unrecognized sources of uncertainty, potentially accelerating the experiential learning process central to developing effectual expertise. Further, Ramoglou et al. (2025) suggest that humans and AI can share the cognitive work of entrepreneurship, where AI broadens the range of possible ideas while human judgment filters options unlikely to become real opportunities. However, the extent to which AI can substitute for experience remains contested, as Townsend et al. (2024) argue that AI's predictive abilities break down in the face of Knightian uncertainty, because some situations cannot be reduced computationally. This suggests that while AI tools may lower barriers to effectual action, they cannot fully replace the pattern recognition and judgment developed through repeated entrepreneurial experience. As the field remains inconclusive on the role of expertise and experience, this becomes especially interesting in a context where novel tools may alter the traditional relationship between experience and decision-making logic.

2.3.3 Resource Availability

Early entrepreneurship research shows that resource scarcity drives founders to adopt creative, improvisational strategies using what they already have (Baker & Nelson, 2005), and prior work on effectuation typically assumes such scarcity (Berends, 2013). Fisher (2012) explicitly links resource constraints to the affordable-loss principle in effectuation: rather than emphasizing expected returns, entrepreneurs assess what they can afford to lose and commit only those resources (Dew et al., 2009a; Sarasvathy, 2001). Consistent with this view, traditional entrepreneurship studies find that startups generally have limited resources for product innovation (Chandy & Tellis, 2000; Moultrie et al., 2007; Millward & Lewis, 2005).

Furthermore, software startups have traditionally been characterized by severe resource constraints, particularly financial scarcity (Giardino et al., 2016; Wang et al., 2016). These constraints shape development practices, where speed is prioritized over quality, corners are cut to develop faster, and cost associated with cutting corners accumulates strategically to enable rapid iteration (Seaman, 2011; Giardino et al., 2016; Klotins et al., 2019; Ries, 2011). In this resource-scarce environment, the team often becomes the primary asset (Kemell et al., 2020), embodying the means-driven logic central to effectuation. As GenAI tools increase coding efficiency (Peng et al., 2023; Batista et al., 2024), and as VC investment inflows remain high (State of European Tech 2025, 2025; Dealroom, 2024), the conditions in regard to financial resources underpinning prior research are called into question for our context. Moreover, Rady et al. (2025) also found that, up to a point, leveraging AI hype helps startups secure investor resources and could potentially improve startup valuations, but beyond a certain threshold it becomes a liability.

While affordable loss is typically framed in financial terms, Dew et al. (2009b) propose an interesting dimension of affordable loss, the distinction between time and money as resources. They theorize that losses paid for in time may be experienced as more affordable than losses paid for in money because their ambiguity allows more flexible mental accounting. They propose that when entrepreneurs account for investments in time rather than money, they may perceive higher levels of affordable loss. The shift in relationship between resource scarcity and effectual logic might have changed in the context of early-stage AI ventures, which calls for re-evaluation of previous literature for entrepreneurs in this context.

2.4 Summary of Literature Review & Theoretical Framework

Effectuation theory has previously been studied and theorized under conditions of high uncertainty, scarce resources, and experienced entrepreneurs (Sarasvathy, 2001; Fisher, 2012). Yet AI-based software startups operate under nearly opposite conditions, where rapid prototyping can reduce development costs, capital is comparatively abundant, and founders are increasingly young and inexperienced (Peng et al., 2023; Dell'Acqua et al., 2023; Batista et al., 2024; State of European Tech 2025, 2025; Dealroom, 2024; Weiss, 2025). At the same time, AI tools reshape the structure of uncertainty itself, reducing local uncertainty through improved prediction while expanding global uncertainty by increasing the range of possible actions (Ramoglou et al., 2025; Townsend & Hunt., 2019). These shifts call into question whether effectuation's traditional antecedents still hold and whether its principles manifest differently when the core constraints of venture creation are transformed.

3. Methodology

3.1 Research Philosophy & Logic

This paper is applying an interpretivist epistemology, focusing on how and why founders behave in certain ways, aiming to understand their perspectives and beliefs (Bell et al., 2022). Moreover, this decision is grounded in the fact that we have a constructivist ontology (Bell et al., 2022), believing that reality is based on the individual person's experiences and cognitive schemas. We adopt a constructivist position wherein entrepreneurial realities, such as *'feeling'*, *'prioritization'*, or *'uncertainty'*, are socially constructed through founders' own experiences, language, and interpretations, and no single objective reality exists to uncover, but multiple subjective meanings are discussed. Moreover, the reasoning behind this paper follows an abductive logic (Timmermans & Tavory, 2012; Bell et al., 2022), working iteratively between existing literature, theoretical concepts, and collected data. Rather than testing predefined hypotheses, the analysis seeks to develop theoretical insights grounded in the empirical narratives of founders, while aiming to extend prior literature.

3.2 Research Design

This research is conducting an interview-based qualitative study with a thematic analysis (Bell et al., 2022), conducting 17 semi-structured interviews, with early-stage AI-based software startup founders in Sweden. This approach not only aligns with our research philosophy, it has also been used in previous research on effectuation (Hubner et al., 2021; Klenner et al., 2021; Nielsen & Lassen, 2012). The unit of analysis is the individual founder, as the study focuses on their subjective reasoning and cognitive processes rather than on organizational structures or outcomes, placing the level of analysis on the individual, micro level, within an organizational context (Bell et al., 2022). Furthermore, applying a thematic analysis allows for identifying both unique patterns within individual founder narratives, as well as shared patterns across founders, identifying how different founders view similar challenges in the same context, the Swedish early-stage AI startup scene, through utilizing a thematic analysis (Bell et al., 2022; Braun & Clarke, 2006). This approach provides a rich, contextualized understanding of effectuation logic in practice.

3.3 Sampling

3.3.1 Recruitment and Access

The interviewees were selected through purposive sampling (Bell et al., 2022) via the Founders House network, an AI-focused hub for early-stage entrepreneurs (Founders House, 2025). Founders House is relevant to this research because its members are pre-vetted for their potential to build innovative and scalable AI ventures. Although this study does not examine the relationship between entrepreneurial success and decision logics, it is important that the participating startups have been assessed as having potential. This means that the decision-making logics we study are developed in ventures that external stakeholders see as somewhat viable.

Through our professional roles, we had direct access to Founders House, which gave us access to early-stage AI founders. This insider position helped us build trust and a good relationship with participants and may have enabled a level of openness and depth in the interviews that would be harder to achieve as external researchers. At the same time, our connection to the organization can introduce risks of bias and blind spots. To address this, we kept reflexive field notes after each interview, where we documented our assumptions, prior knowledge, and emotional reactions. We also held peer debriefing sessions to discuss how our affiliation with Founders House might influence our interpretations and to identify possible biases in data collection and analysis.

3.3.2 Inclusion Criteria

In order to ensure relevance an inclusion criteria was developed;

1. The participant must be a founder or co-founder with active decision-making authority over product decisions and must currently be operationally involved in the startup.
2. The participant must lead a startup whose primary offering is an AI-based software product or service.
3. The participant must operate an early-stage venture, defined as having raised pre-seed or seed funding but not yet Series A.
4. The startup must be Sweden-based.

We did not use age as an inclusion criterion, but we recorded it as background information to describe the sample. However, since Founders House explicitly targets the next generation of young founders (Founders House, 2025), our pool of participants was relatively young. This was intentional, as it reflects a broader trend in early-stage AI startups and offers an opportunity to explore how relatively inexperienced founders make decisions. We also sought diversity in AI application areas (for example, B2B vs B2C, and different industries), but this was not a strict inclusion criterion. Instead, variation in application areas emerged naturally within the Founders House network.

Criteria (1) ensures that the person interviewed can describe and reflect on their own experience and decision-making around product decisions, as well as have direct impact on the company. By sampling entrepreneurs who are currently in the midst of making such decisions, we minimize the need for long-term recall, which Koller et al. (2025) criticize as a weakness in earlier work (e.g., Chandler et al., 2011; Werhahn et al., 2015). Longer recall periods increase the risk of rationalized recollections, leading to causation logic (Podsakoff et al., 2003; Koller et al., 2025; Reymen et al., 2015). Criteria (2) ensures that the startups are AI-based, software focused and operate close to the current AI wave. This allows us to consider their specific context in terms of funding, tools, markets and competition. We define AI-based software startups (Vásquez et al., 2026) as those where artificial intelligence (specifically machine learning, large language models or GenAI) is core to the product's value proposition, rather than a minor feature or backend optimization tool. Criteria (3) focuses on early-stage ventures so that founders still hold dominant decision-making power, rather than decisions being widely distributed across a larger organization. With pre-seed and seed funding being investment rounds given to ventures that are validating and developing their product, while later stage investments (referred to as Series A) are given to ventures that have already raised money (De Clercq et al. 2006). Early-stage startups also operate under high uncertainty and do not yet know which decisions will lead to success (Alvarez & Barney, 2005; Giardino et al., 2016). Criteria (4), including only Sweden-based founders, is motivated by our access through the Founders House network and by Sweden's role as a leading AI startup hub, ranking as the 4th country globally in private investment in AI (WIPO, 2025; Stanford HAI, 2025).

3.3.3 Sample Overview

The sample size of 17 founders was determined by thematic saturation, where new interviews no longer added substantial new insights. The final sample consists of 11 male and 6 female founders, broadly reflecting the current gender distribution in the Swedish AI startup ecosystem, where only 10% of VC funding goes into female-founded startups (Dealroom, 2024). We sought diversity where possible within these constraints but acknowledge this imbalance and consider its potential implications in our analysis.

To ensure anonymity, the individual cases are presented in a generalized form. Given the relatively small and visible Swedish AI startup ecosystem, we have intentionally broadened descriptions of startup focus and sector, reported founders' ages in ranges (overall range being between 20-32 years old), and not disclosed exact amounts of funding raised. Although this reduces the level of detail, we judged that this level of anonymity was necessary to prevent identification of participants and to encourage more open and honest sharing during the interviews.

Table 1. Overview of Sample

Interview length in minutes	**Pseudonym**	**Gender**	**Age range**	**Role**	**Startup Focus**	**Company Stage**	**Team size**
48	E1	Male	20-23	Co-founder / COO	AI-focused B2B Product	Pre-seed	3-4
68	E2	Male	30-32	Co-founder / CEO	AI-focused B2B Product	Seed	4-5
70	E3	Male	24-26	Co-founder / CEO	AI-focused B2C Product	Pre-seed	2-3
62	E4	Male	20-23	Co-Founder/ CEO	AI-focused B2C Product	Pre-seed	4-5
50	E5	Male	24-26	Co-founder / COO	AI-focused B2C Product	Pre-seed	3-4
52	E6	Male	24-26	Co-Founder / COO	B2B/B2C Agentic AI product	Seed	5-7
69	E7	Female	20-23	Co-founder / CEO	AI-focused B2B Product	Pre-seed	2-4
72	E8	Female	27-29	Co-founder / CEO	AI-focused B2C Product	Pre-seed	2-3
67	E9	Female	27-29	Co-Founder / CEO	AI-focused B2B Product	Pre-seed	2-3
68	E10	Female	30-32	Solo Founder	AI-focused B2B Product	Pre-seed	1-2
46	E11	Male	27-29	Co-founder / CEO	AI-focused B2B/B2C Product	Pre-seed	1-2
49	E12	Male	24-26	Co-founder / CEO	AI-focused B2B Product	Pre-seed	4-5
59	E13	Female	20-23	Co-founder	AI-focused B2C Product	Seed	1-2
67	E14	Male	20-23	Co-founder / CEO	B2C Agentic AI product	Pre-seed	1-2
70	E15	Male	20-23	Co-Founder /CEO	AI-focused B2B Product	Seed	5-7
60	E16	Male	30-32	Solo Founder	AI-focused B2B Product	Pre-seed	1-2
45	E17	Female	20-23	Solo founder	AI-focused B2B Product	Seed	3-4

3.4 Data Collection

Data were collected through semi-structured interviews of approximately 60 minutes (range 46-72 minutes). Interviews were conducted either in person (10) or via video call (7), depending on participants’ preferences and availability, and we observed no clear differences in depth or openness between these formats. In total, we conducted 17 interviews with 17 different founders and companies, from our sampling frame. We used an iterative approach, conducting preliminary thematic coding after every 4-5 interviews to monitor emerging patterns and decide whether further data collection was needed. Thematic saturation was reached after 17 interviews, as themes stabilized after interview 13, with interviews 14-17 primarily confirming existing patterns.

Semi-structured interviews were chosen to balance comparability across participants with flexibility to explore individual experiences in depth, which aligns with our interpretivist stance. A pilot interview was conducted to refine the wording, order and scope of questions. The interview guide was organized around eight thematic blocks, designed to move from contextual grounding to in-depth reflections on decision-making, emotions, and cognition. Consistent with our interpretivist stance, the interview design prioritized eliciting founders' subjective sense-making rather than seeking objective 'facts' about decision outcomes. Questions were deliberately open-ended and focused on specific, recent prioritization decisions (same day, week or month), and on a narrow decision context (feature prioritization), to address concerns about broad, long-term recall in earlier effectuation studies (Koller et al., 2025), as well as allowing participants to construct their own narratives about prioritization dilemmas. The guide remained flexible throughout data collection, so new topics could shape later interviews. For example, after four interviews revealed unexpected benefits from AI tools, we added follow-up questions about their use and impact. Furthermore, each section aimed to elicit rich, narrative-based data while maintaining logical flow and psychological safety for participants.

Table 2. Overview of the Interview Guide (see full interview guide in Appendix B).

Section	Theme	Main Question
Context	AI-context	How do you experience building an AI-focused startup specifically?
Anchor Episode	Recent feature-prioritization decision	Think of the last time you chose what to build (or cut). Walk me through the timeline: trigger, options, actions, decision.
Emotions & Affect	Emotional experience of product decisions	During high-stakes product decisions, what emotions show up for you? How do they help or hinder your choices?
Cognition & Decision Logic	Heuristics, intuition, and analytical reasoning	When you prioritize between features (or actions), how do you balance intuition vs analysis?
New Product Development Process	From idea → prototype → ship → iterate	What's your current New Product Development timeline; from idea → prototype → ship → iterate?
External Factors & Constraints	Stakeholders, pressures, and resource limitations	Which outside forces / external stakeholder most shape your decisions/prioritization today?
Intentionality, Meaning & Criteria	Personal values and criteria for building	What makes a feature worth building for you? If you had to write the top 3 criteria on a whiteboard, what would they be?
Closing Reflections	Evolution and meta-insights	What have you changed in your prioritization approach in the past year? What would future-you advise current-you?

3.5 Data Analysis

3.5.1 Thematic Coding

The analysis follows Braun and Clarke's (2006) six-phase framework for thematic analysis:

1. Familiarization with data
2. Generating the initial codes
3. Looking for themes
4. Reviewing the themes
5. Defining and naming the themes
6. Producing the final report

Coding was first conducted openly to capture participants' own meanings, then iteratively linked to key effectuation constructs; means-driven action, affordable loss, stakeholder relationships, and contingencies (in line with Read et al.'s (2009b) conceptualization) with control being viewed as an overall logic (Sarasvathy, 2001). Each founder's narrative was analysed individually to keep the context and identify unique patterns. Scape was used to transcribe the interviews while recording (Scape, 2025), then we listened to the recordings and corrected the transcripts. We highlighted interesting quotes by hand, added notes on links to theory, and then transferred relevant quotes and notes into a Google Sheet, where they were grouped into broader themes. While we follow Braun and Clarke's (2006) general approach to thematic analysis, we use Gioia et al. 's (2013) three-tier structure to move from informant terms (first-order codes) to researcher categories (second-order themes) and broader theoretical dimensions (aggregate themes).

Table 3. Examples of coding

Examples of Coding					
Quotes	Interviewee	First-order code	Second-order code	Third-order code	Connection to theory
"Timing and urgency is the key component that will help us win"	E9	The need to move fast with urgency in order to succeed	Speed as competitive moat	Speed	Perceptions of the AI space
"Keep in mind what customers know and are comfortable with using"	E14	Understanding what customers want and know	Prioritizing customers' needs	Customer collaboration	Pre-commitment
"AI coding tools for sure. Like, I mean, it's 100% like life-changing."	E16	AI tools as the biggest change in building products in the AI age	AI tools as important tools for building	Excitement for AI technology as available means	Means-driven logic

Initially, we generated 668 lines of code from the 17 interviews. Each interview was read three times: (1) while adjusting the transcript and writing initial notes, (2) during individual reading and highlighting by both authors, and (3) in a joint discussion of each interview and its main insights. After analyzing all 668 lines of code, relevant quotes were compiled in a google spreadsheet (see a selection of the list in Appendix C), which we then used for cross-case comparison (Bell et al., 2022). The analysis followed an abductive logic, moving back and forth between data and theory. Existing theories served as lenses for understanding founder decision-making but were not imposed as fixed categories. Instead, we let empirical patterns guide how theoretical concepts were used and refined.

3.6 Reflexivity, Trustworthiness, and Ethics

3.6.1 Insider Position and Reflexive Practice

Since we access participants through the Founders House network, we hold an insider-researcher position. This can increase trust, openness and contextual understanding, but also introduces risks such as social desirability and bias from pre-existing relationships. To address this, we kept reflexive notes after each interview (see examples in Appendix D), where both authors documented preconceptions, emotions and contextual observations. We each analysed the interviews independently before discussing our interpretations, to reduce group thinking and founder-specific bias. We also limited how much we shared about prior findings during interviews, to avoid steering participants' answers. Finally, we are transparent in the write-up about our role and its possible influence on data collection and interpretation, in line with criteria of methodological rigor (Lincoln & Guba, 1985).

3.6.2 Credibility, Transferability, Dependability, Confirmability

We ensure methodological rigor using the four classic qualitative criteria by Lincoln & Guba, (1985); credibility, transferability, dependability, confirmability.

Credibility

Credibility concerns how truthful and plausible the findings are in relation to participants' lived experiences (Lincoln & Guba, 1985). We used several strategies to strengthen credibility. First, we interviewed founders from different AI-focused startup types, which allowed us to see which patterns recurred across cases while still noting unique experiences. Second, we conducted member checking with five purposely selected participants (Birt et al., 2016), where these participants were asked whether our interpretations reflected their views and decision-making. They confirmed the core themes, and two highlighted that we had downplayed the hype around AI as a way to secure early customers, which we then integrated into the final analysis. Third, both authors attended each interview and independently reviewed and coded the transcripts before discussing interpretations and theoretical links, challenging each other's assumptions to reduce single-researcher bias. We also held regular debriefing meetings with our thesis supervisor, who questioned our emerging interpretations and helped identify blind spots linked to our insider position in the Founders House network. However, we strongly believe that our insider position provided us with more rich data, and honesty from the interviewee, that would otherwise be hard to achieve.

Transferability

Transferability refers to the extent to which findings can be meaningfully applied in other contexts (Lincoln & Guba, 1985). In a qualitative, interpretive study like this, the aim is not statistical generalisation, but to give enough contextual detail for readers to judge whether the results are relevant to similar settings. We therefore provide "thick description" (Geertz, 1973) at the ecosystem and thematic level, rather than at the level of individual people or companies. This includes descriptions of the AI landscape, common features of effectuation, and typical challenges founders face product decisions. Individual participants and startups remain fully anonymous. Contextual information such as product category, use case or stage is aggregated, generalised or slightly altered to avoid indirect identification.

Dependability

Dependability relates to the stability and transparency of the research process over time (Lincoln & Guba, 1985). To ensure dependability, a systematic documentation process, and digital audit trails, are maintained throughout the project, only accessible by the two authors and examinator upon request. This includes:

1. Records of interview procedures (transcripts, dates, contexts, and researcher reflections)
2. Versions of the interview guide as it evolved
3. Memos from coding sessions and theoretical discussions
4. Decision logs showing how analytical categories were refined over time.

This continuous documentation ensured the study's overall dependability. However, transcripts are not added to the appendix to ensure anonymity of the interviewed founders.

Confirmability

Confirmability concerns the extent to which findings are shaped by participants rather than researcher bias or motivation (Lincoln & Guba, 1985). Given our insider position within the Founders House network, explicit reflexive strategies are important. First, we kept a reflexive journal after each interview, documenting preconceptions and contextual observations. This helped us identify potential biases and reflect on how our background in the Swedish startup ecosystem might colour our interpretations. Second, we wrote reflexive memos during coding to record our reasoning behind theme development and theoretical links. Third, we kept a digital audit trail from raw transcripts to the final thematic structure, ensuring traceability of our analytical steps. Taken together, these measures support that our conclusions are grounded in founders' narratives and a systematic, transparent analysis, rather than our own preconceptions.

3.6.3 Ethical Procedures

All participants provided informed consent before each interview. As a master's thesis at Stockholm School of Economics, the study did not require formal ethics board approval, but the research design was reviewed and approved by our thesis supervisor to ensure compliance with SSE's ethical standards and GDPR. Interview recordings and transcripts are stored on encrypted, SSE-approved cloud storage (Google Drive via SSE accounts), accessible only to the two researchers. Data is processed and stored in accordance with GDPR (European Union, 2016) personal identifiers, company names and sensitive operational details are removed or pseudonymised during transcription. Participants could withdraw at any time without giving a reason, in which case their data were deleted. In line with SSE's data-management rules, data are kept securely until the thesis has been examined and graded, after which all raw recordings and identifiable material will be permanently deleted (Stockholm School of Economics, n.d.).

4. Findings

4.1 Introduction to Findings

This section presents findings from the interviews, using Sarasvathy's (2001) effectuation theory and its principles as the main analytical lens. We focus on how founders reason about product decisions and which features to include or exclude. The findings suggest that effectual logic is still present, but appears in reconfigured forms shaped by the current environment and by characteristics of today's founders.

The application of an constructive ontology (i.e. their perceived reality is their reality they live) makes the perception of the founders central, particularly regarding access to financing and confidence in raising additional capital, increased market speed, and heightened uncertainty. Apart from the evidence presented on the current landscape, their perceptions can be found in the interviews as well:

"With this hype, fundraising is more accessible than ever. I feel that many companies raise early and quite a lot of money as well." - E2

A selection of more illustrative quotes not brought up in the finding section, both on the perception of the environment, and the principles, are provided in Appendix C.

4.2 Means-Driven Logic

Founders consistently demonstrated means-driven logic when reasoning about product possibilities. Rather than beginning with predetermined market goals and working backwards, founders articulated their decision-making as starting from their own capabilities, the team, and the technological means available to them.

"It's a very creative process of building features. So one part is like inspiration from other tools you have used. One part is you get feedback from customers. Sometimes it comes from you and your experience, you just get creative." - E1

This manifested particularly in how founders talked about LLMs and GenAI tools provided by major technology companies. Founders framed opportunities through imagining what could be built with available technologies rather than through market analysis. The logic followed "what can we create with these capabilities?" rather than "what should we build to capture this market?"

"So the possibilities of ideas and building a valuable product are much greater now when we can build an AI startup. There are so many unexplored combinations of technology and use cases and areas. There are more possibilities of creating value than creating a startup that is not with AI because people have done that for so many years." - E6

GenAI tools played a central role in this reasoning. Founders emphasized how these tools expanded their conception of what was possible to build, effectively enlarging the set of means from which they could reason. The tools didn't just enable faster execution, but they fundamentally shaped how founders thought about the opportunity space itself.

"I don't think we would be able to do this without AI to be honest. I've never built an app or a web app before so having those tools and just being able to iterate really quickly on the products and get something out there really quickly." - E5

Several interviewees expressed how they use GenAI or agentic AI as collaborative partners in decision-making processes.

"And when it comes to AI there, we sometimes consult like Gemini agents who has like the context of pretty much everything about our company and the place we're at and what to prioritize." - E5

"What's been interesting with building agents is that it's kind of trying to explore itself, right? It kind of realizes, okay, I need this to accomplish this. So essentially most of the decisions is taken from the system itself (...) I would really see it as like our agentic system is a person in the decision-making process almost (...)it's easy to make the quick like small wins (...) it's not gonna come up with (...)a whole new system." - E14

However, founders also understood the limitations of AI tools, underlining that AI is one of many tools and means in their stack, emphasizing the importance of maintaining control in decision-making.

"AI becomes a tool rather than a co-thinker. Right? In the end, you want the control and you want to be the director of what happens, especially in regards to code." - E4

Particularly striking was how founders rejected traditional decision-making frameworks common in entrepreneurship. Founders dismissed industry templates and long-term planning models as inappropriate for their context, reflecting a cognitive stance that such predictive, goal-driven frameworks didn't align with how they reasoned about building in an environment where the future was difficult to predict.

"Now it feels like there's a lot of group thinking going on [in the AI industry]. There should be certain activities, certain ways to do stuff. And it doesn't really push your creative boundaries to a point where you actually come up with something intuitive." - E2

"I can have a general sense of where I think [technological development] is going and I'm building products with that in mind, but that comes down to being adaptable, you know. A general vision is good, but I don't have a super clear end goal. The only truth is what is now, and what the users want." - E13

The means-driven logic acknowledged fundamental unpredictability. Rather than viewing this as an obstacle requiring better forecasting, founders incorporated it into their reasoning. They leveraged technologies, tools, and capabilities at hand, and reasoned forward about what could be shaped. This was supported by AI tools, both as a means of creating the product, and a support for making decisions, although caution, emphasising control.

4.3 Affordable Loss and Control-Centered Logic

The affordable loss principle in classic effectuation centers on reasoning about acceptable downside risk, typically framed financially. In the AI-focused software startup context, however, founders' risk reasoning followed fundamentally different logic, revealing an absence of financial constraint framing alongside pronounced emphasis on temporal constraints and deliberate resource limitation.

4.3.1 Temporal Over Financial Risk Reasoning

When discussing feature decisions, directions to pursue, or commitments to make, founders notably did not explicitly articulate reasoning through financial risk calculations. If anything, founders demonstrated willingness to make larger bets, reasoning that because building costs had decreased dramatically due to AI tools, they could build in one direction and scrap it later without significant financial consequence.

"So let's say you have an idea for a feature that is really, really cool. Now with AI, you could do that one in one week, release it, get feedback, and let's say it's a totally bad feature. Then you know it already after one and a half weeks. But if it was two years ago, then you've wasted four weeks and resources." - E6

Instead, the primary constraint shaping affordable-loss reasoning was time. Nearly all founders articulated decision logic centered explicitly around temporal limitations. They reasoned about what they could afford to lose in terms of time investment, asking "can we afford to spend weeks or months on this?" rather than "can we afford to spend this capital?"

"For us, [the biggest constraint] is definitely time. So money is not the biggest problem right now since we got the funding and we don't have that much we need to spend money. And it's so much time pressure." - E11

This temporal focus emerged from founders' reasoning about their context. They recognized that building costs had decreased substantially due to AI tools, reducing financial risk of experimentation. Simultaneously, they perceived that ecosystem speed had increased the opportunity cost of time.

"If you go in with the mentality that everything you do might be scratched tomorrow, I think that helps you get out of analysis paralysis and make certain decisions because if you just assume whatever you're going to do might be rewritten or be wrong anyways." - E2

Features taking months or weeks could become obsolete due to competitors or new model releases. Founders therefore treated time as their scarcest resource, requiring protection and careful allocation.

4.3.2 Control Through Strategic Resource Constraint

The absence of traditional financial resource constraints also shaped how founders applied control-centered logic. Because AI tools increased their ability to build more, and the development in the space opened up many opportunities, this sometimes led to more decision uncertainty, as the options felt endless.

> *"I mean, [AI tools] have pros and cons. It's good to test fast, but of course, we run into that issue of having too much to build. There's a risk of overloading the app. So in a way, AI negatively impacts the process of building a clean app because there's just too many options and too much to do." - E4*

A particularly revealing manifestation emerged in how founders reasoned about team size. Despite having financial capacity to hire, founders deliberately kept teams small to constrain their resources on purpose. By keeping teams small, founders reasoned they could maintain quality control, stay focused on building genuine value, and retain direct influence over the venture's direction.

> *"We've stayed very lean on purpose in the earlier stages even though we've grown. And the bigger team is not necessarily good because the product will get more dispersed. You will lose control. You will lose focus on the core. And we're not [limiting team size] from a financial standpoint, it's about finding the right talent. The right talent becomes even more important because then one person's outcome is 10 times bigger." - E6*

Founders articulated interconnected reasons for this logic. AI tools had amplified individual productivity; one person was no longer responsible for the same output as before. Small teams allowed them to keep uncertainty manageable, retaining direct influence over outcomes and maintaining control over the venture's direction.

"I can work on two totally separate features on our platform at the same time. So I could have two agents in GitHub Co-pilot, which I've done today, one of them works on [one feature], as well as having one working on [another feature]. And I mean, that hasn't been physically possible without hiring someone else before." - E3

This deliberate limitation served to constrain the isotropic uncertainty created by the increase in possible decision paths. Founders reasoned that with tiny teams, they were forced to build based on immediate means. The logic was circular but coherent, limit your means and resources to maintain control, and that limitation reinforces control.

"I think it makes it even more important that you are very focused and very intentional on what you do. And that's like a reason why we have kept the team so small despite raising quite a lot of funding is that because we are limited in what we can do then, and we have to be very, very intentional with our time." - E1

The affordable loss logic thus operates on multiple levels. Founders reason about temporal rather than financial constraints when evaluating acceptable downside. They deliberately limit means, keeping teams small despite financial capacity, to maintain controllability and manage uncertainty and stay flexible. Both patterns reflect the core affordable-loss principle of limiting downside risk, but the specific manifestation is shaped by context, where reduced building costs and more capital shift risk from financial to temporal, while AI-amplified productivity results in control through strategic resource constraint.

4.4 Pre-Commitment Logic

Founders demonstrated clear pre-commitment logic, reasoning about shaping ventures through stakeholder collaboration. However, this was limited almost exclusively to users and customers to co-create products. They reasoned about product development as an interactive process of building with committed early adopters. They also identified how this is aided through AI tools and as a way to maintain control due to the isotropic uncertainty the AI field and AI tools create.

"And I think building with all of these tools, I think it's the most important thing to keep in mind is just to build for the customers. In the end, you're building something that should have as few as possible functions in it with as much value as possible. I think the customer is absolutely central in that decision process." - E14

"(...) the users will figure out the problems and use cases. It's customer co-creation… and that is how our users have a lot of creativity themselves…and then they will see a bunch of different scenarios… problems that we didn't even know about. - E6

Examining the full scope of stakeholder commitments revealed a striking pattern, where pre-commitments were concentrated almost exclusively on customers and users, not on the diverse stakeholders featured in traditional effectuation research. Founders did not articulate reasoning about building commitments with investors, suppliers, or institutional partners. Instead, their pre-commitment logic focused narrowly on early users functioning as co-developers.

"Customers. 100%. That should always be the main focus. It doesn't matter what anyone else says. If the customers have a problem, that's what you should solve." - E11

Some interviewees also expressed that relying on customer co-creation and feedback was a way of acknowledging their inexperience, putting even larger emphasis on listening to customers.

"I think it can be both for the good and for the bad [to be young and inexperienced], that you come in with a very blank page. So that forces you to really listen to customers. Which I think is a good thing because, especially now with like LLMs and everything, it is very different. And everybody is new to AI. So I think it's like the most important thing is to learn fast." - E1

Two contextual factors enabled this user-centric pre-commitment logic. First, founders recognized that AI tools had fundamentally changed the speed at which they could build prototypes and testable features. This shifted when pre-commitments could occur. Rather than waiting until later stages to have something concrete, founders could engage users at the earliest stages, building and testing rapidly with early customers.

"[The use of Generative AI coding tools] is more of a shortcut than it is like a fundamental shift in how you build, I think. It's more like a shortcut to that first meeting." -E10

This rapid prototyping capability addressed what previous research identifies as a significant challenge for early-stage software startups, requirements engineering. Because they could build, iterate, and prototype quickly, requirements engineering happened simultaneously with customer involvement rather than sequentially. They didn't need to fully specify requirements before engaging users, instead, they reasoned about building and learning with users in rapid cycles.

Second, founders recognized that AI hype created unusual customer curiosity and willingness to engage early. When reasoning about why they could secure early user commitments, founders pointed to the environmental factor that potential customers were intrinsically interested in trying AI products and helping shape them.

"I think with AI like what I've noticed is that because of the timing of it, customers are very interested in talking to you. And in our specific case because we are targeting like a very old school industry, I think what we do with AI just feels like it's like magic for them, and they become more excited because of that." - E9

AI-based founders reasoned that the technological moment itself created favorable conditions for building user commitments. The pre-commitment logic thus remains fundamentally effectual, but is narrowed primarily to users as co-developers, while commitment-building timing shifts even earlier in the venture lifecycle.

4.5 Contingency Logic

Founders demonstrated significant contingency logic, but how they reasoned about flexibility and unexpected events was deeply shaped by their technological context, both the tools available and the rapidly evolving landscape. Founders articulated a strong orientation toward flexibility and being alert. They reasoned about remaining adaptable and using unexpected events as opportunities, a cognitive stance mediated by their access to GenAI tools. Because these tools enabled faster building and higher-pace iteration, founders could act on unexpected developments with high speed and without committing substantial time or financial resources.

"The cost of iterating and building has gone down, that also means that for me, being flexible and adapting to what's happening around me is quite cheap. But it is a tradeoff, when everything is about speed you want to run fast, but also be able to change direction fast. But this is probably easier for me than say [industry incumbent]." - E17

Founders reasoned that they could build different things in parallel, leveraging available tools, which reinforced a flexible cognitive orientation. The knowledge that these capabilities existed, that they could rapidly shift direction or test multiple approaches simultaneously, shaped their logic around product decisions.

"You can run multiple processes in parallel or ideating or getting examples of how to write code and editing it in your way. It allows you to be fast and try out new things and be responsive. I mean, when it comes to using the models, that's the new way of building companies, right? Everyone is doing it." - E12

The contingency logic extended beyond capability to also include how founders reasoned about their environment. Feature priorities shifted daily or weekly in response to new AI model releases, emerging capabilities, and evolving technologies. Founders didn't view this rapid change as problematic. Instead, they reasoned that there was no purpose in staying rigid.

"We are guided by technological shifts, which is external forces, right? New models, we have picked up GPT-5 and switched a little bit between Gemini and Claude Opus to try out model performance which is guided by what is released. We immediately jumped on OpenAI's real-time voice model when it came out. We are to a high extent guided by this. You need to be aware of these technological shifts and stay flexible in your iteration process." - E12

Founders recognized they operated in a landscape where the technological foundation itself evolved at high speed. New LLM releases presented completely new capabilities that could fundamentally change what was possible to build. Rather than viewing this as creating instability, founders embraced these developments, reasoning about them as opportunities to disrupt slower-moving incumbents.

"It's crazy. We're always on our toes when there's a new model coming out from the big ones. The new models are significantly better every time so it could make our product twice as good instantly. We stay alert, incorporate in our product, and make necessary changes." - E13

However, founders also articulated tensions within their contingency reasoning. Despite AI tools and lower switching costs, founders acknowledged reluctance to "kill their darlings," to abandon features or directions they had invested in. Additionally, founders recognized that market speed created enormous pressure to build fast and stay flexible simultaneously, framing this as a genuine challenge.

"Speed as a moat [i.e. competitive advantage] *really means that you are way more stressed. Staying ahead of the curve at all times, given the speed at which our industry [name of industry]-AI develops is taxing sometimes." - E4*

Despite these tensions, the overall contingency logic remained strong. Founders consistently reasoned about technological uncertainty as something that forced flexibility rather than something that could be overcome through better prediction, which was also their strength towards bigger players in the market.

"And people that have been in the game for a while are not used to that, which stirs the pot a bit, regarding who can take advantage of this change." - E3

The contingency logic thus represents an amplified manifestation of the lemonade principle. Founders reason about flexibility as both a capability, enabled by AI tools, and necessity, required by rapid technological evolution. Their cognitive orientation frames unexpected events, particularly new technological capabilities, as opportunities rather than obstacles.

4.6 Instances of Causal Logic

While the findings demonstrate strong effectual logic across all five principles, founders did not reason exclusively through effectuation. At certain moments and in specific contexts, founders employed causal logic, attempting to predict future outcomes and working backward from desired goals. Some founders expressed interest in predicting technological trends to "ride the next wave." However, they simultaneously acknowledged the difficulty and unreliability of such predictions, meaning they didn't rely heavily on this approach.

"I think technology trends are more interesting because that's like, how can you ride the next wave in trying to predict where things are heading. Even though like most cases you will be wrong anyways." - E2

Causal reasoning appeared most prominently when founders discussed broad, overarching visions and goals, which they combined with effectual principles in day-to-day execution.

"One is aligning on the big vision of the project. What is the ultimate goal that we're trying to achieve here?" - E12

Founders also articulated hypothesis-driven approaches in certain situations, formulating predictions about what would work and testing those predictions. However, these predictive reasoning episodes occurred over shorter time horizons rather than the long-term planning characteristic of pure causal logic.

"I think, what tests we do run instead is like we put up hypotheses. Sometimes we want to prove something, and sometimes it's hard to prove something, so we rather say, 'Can we invalidate this hypothesis?'" - E2

These hypotheses and goals were not rigid and operated over shorter periods of time. The hypothesis-driven logic was often tied to experimentation, which aligns with Chandler et al.'s (2011) principles of experimentation. The interplay between effectual and causal logic suggests that founders employed cognitive flexibility.

4.7 Summary of Findings

The findings reveal that effectual logic persists in founders of AI-based software startups but manifests in distinctly reconfigured ways. Founders demonstrate means-driven logic, but reason from a combination of externally provided, rapidly evolving technological capabilities and personal resources. Affordable-loss logic shifts from financial to temporal constraints, with founders deliberately limiting team size to maintain control amid expanded resources. Pre-commitment logic narrows almost exclusively to users as co-developers, enabled by rapid prototyping capabilities and heightened customer curiosity. Contingency logic is amplified, with founders embracing technological evolution as opportunity rather than obstacle. While causal reasoning appears in bounded contexts around broad goals and short-term hypotheses, the effectual logic is highly present.

5. Analysis and Discussion

Founders in our sample demonstrated all five of Sarasvathy's (2001) effectual principles (means-driven logic, affordable loss, pre-commitment, contingency, and an overall focus on control), alongside instances of causal logic. This resembles Nguyen-Duc et al.'s (2021) study on software startups, where effectual logic dominated (71.4% of coded events) but causal logic was also present. It aligns with research showing that effectuation and causation are not mutually exclusive, but complementary (Koller et al., 2022; Smolka et al., 2018; Matalamäki, 2017). Our primary finding is that effectual logic persists, although previously identified antecedents have changed.

5.1 Resource Abundance

Traditional effectuation theory positions resource scarcity as a key driver of affordable-loss reasoning (Berends, 2013; Fisher, 2012; Sarasvathy, 2001). Founders in our sample, however, showed strong effectual tendencies in product development decisions despite perceiving having substantial financial resources, as they explicitly stated that they are confident in access to financial resources (section 4.1, E2), reflecting the general trend of VC investments in AI (State of European Tech 2025, 2025; Dealroom, 2024). This also supports the recent findings of Rady et al. (2025), showing that AI hype can be leveraged to secure investor means and increase valuation. This section examines how the principles of effectuation played out under conditions of relative capital abundance, with focus on the principles affordable-loss logic and control-oriented mechanisms (*Pilot-in-the-plane* (Sarasvathy, 2001)).

5.1.1 Time as the Main Currency in Affordable-Loss Decisions

Founders applied affordable-loss reasoning through time rather than money when making product development decisions. The underlying cognitive calculus (determining what one can afford to lose) remained the same, but the currency shifted from financial to temporal, as exemplified by E11 in section 4.3.1. This temporal focus appears to reflect founders' recognition of reduced building costs, enabled by AI tools, as well as access to VC capital, while combined with a strong focus on time-limits. Founders showed willingness to make larger experimental commitments, reasoning that product directions could be pursued and abandoned without significant financial consequences, as illustrated by E6 in 4.3.1, and in that shows some causal logic. However, risk calculations mainly centered on time investment rather than capital expenditure, which was affordable-loss centered. This pattern also aligns with Koller et al.'s (2022) finding that low-cost, high-complexity decisions drive effectual logic through experimentation, where AI tools make product feature decisions more efficient, while maintaining decision complexity through expanded possibilities (Ramoglou et al., 2025; Townsend and Hunt, 2019).

This shift from financial to temporal framing creates tension with Dew et al.'s (2009b) proposition that time losses may be experienced as more affordable than financial losses due to accounting ambiguity, potentially allowing entrepreneurs to perceive higher acceptable loss thresholds. Founders in our sample did not treat time as more affordable due to ambiguity, rather, they treated time as a scarce resource, due to the rapid pace of the market, while financial constraints are perceived as more available. Taken together, this implies that the affordable-loss principle may be driven by the most salient constraint in a given context, not necessarily by financial limits. In our case, time, not money, was treated as the scarce "currency," which contrasts with Dew et al.'s (2009b) expectation that time losses are generally perceived as more affordable than financial losses.

5.1.2 Strategic Resource Constraint as Control Mechanism

Despite having the financial capacity to expand teams, founders deliberately maintained minimal team sizes when making product development decisions, as articulated by E6 in 4.3.2. This strategic limitation appears to reflect the control-oriented reasoning central to effectuation (Sarasvathy, 2001, 2008). Here, founders constrain resources on purpose to maintain influence over product direction and quality.

Founders reasoned that AI tools had expanded what they could build, creating decision complexity with heightened isotropic uncertainty, as described by E4 in 4.3.2. This acceleration paradoxically expanded rather than constrained the product decision space (Ramoglou et al., 2025; Townsend and Hunt, 2019), creating what founders experienced as overwhelming feature options. Strategic limitation emerged as a way to constrain this expanded product opportunity space to cognitively manageable levels. As E1 articulated in 4.3.2, deliberate resource limitation enforced intentionality in product decisions. Founders applied this logic across multiple interconnected dimensions, where small teams enabled them to maintain focus and control over product direction (E6 in 4.3.2), while AI tools amplified individual productivity (Peng et al., 2023; Dell'Acqua et al., 2023), making small teams operationally viable for product development (E3 in 4.3.2).

Founders consistently framed this limitation as a strategic choice rather than as a response to scarcity, which raises theoretical questions about the nature of constraint in effectuation. Traditional accounts present resource scarcity as an external condition that drives effectual logic (Reymen et al., 2015; Fisher, 2012; Berends, 2013). Our observations instead suggest that constraints can be strategically constructed rather than only externally imposed and is a way to exert control. Founders create limiting conditions to manage decision complexity, and possibly create more creative, improvisational strategies with resources at hand, which Baker & Nelson (2005) found was a consequence of resource scarcity. This resembles an active use of the control principle (Sarasvathy, 2001) and an intentional reinforcement of her means-focused logic. It could also be interpreted as affordable loss logic, as they are minimizing downside risk of hiring more developer manpower, instead of maximizing upside. It is still unclear whether founders set these constraints because they are consciously trying to use effectual logic, or if it's just a practical way of working that happens to look effectual.

5.2 Limited Experience, Customer Co-Creation and AI-Augmented Capabilities

Sarasvathy's (2001) seminal research is based on her doctoral studies where she interviewed expert entrepreneurs averaging 15 years of experience, positioning expertise as a key driver of effectual logic (Dew et al., 2009a; Read et al., 2009b). Founders in our sample, notably younger with less extensive entrepreneurial experience, nevertheless demonstrated effectual decision-making in product development across multiple principles. While some prior research has shown that novices can employ effectual principles (e.g., Politis et al., 2010), the specific ways this plays out in the AI context contribute to ongoing scholarly discussion about experience as an effectuation antecedent.

5.2.1 Customer-Centric Pre-Commitment in Product Development

Pre-commitment logic (Sarasvathy, 2001) in product development manifested through intensive customer co-creation, with founders concentrating stakeholder commitments almost exclusively on customers rather than diverse stakeholder types. Interestingly, founders explicitly framed inexperience as a reliance on customer input for product decisions. As E1 articulated in 4.4, that coming in with a "*blank page*" forced customer listening, which assumed particularly valuable when "*everybody is new to AI.*" Moreover, AI tools have enabled earlier customer engagement through rapid prototyping capabilities (E10 in 4.4), allowing founders to gather product requirements and develop simultaneously through rapid iteration cycles, aligning with research on AI tools efficiency and precision (Peng et al., 2023; Dell'Acqua et al., 2023; Batista et al., 2024). This contrast previous software contexts, where startups have developed products with limited user contact and early requirements engineering (Klotins, 2019; Melegati et al., 2019). Additionally, the AI market context created conditions where customer interest temporarily lowered engagement barriers (E9 in 4.4). Although Rady et al.'s (2025) study looked at AI hype in relation to investor pre-commitments, our finding implies that AI hype can aid in securing customer pre-commitments and collaboration.

The concentration of pre-commitments almost exclusively on customers in product development, rather than the diverse stakeholder portfolios which likely reflects both inexperience and contextual factors. Customer focus was shown as the most accessible and immediately valuable stakeholder type for product development decisions for founders with limited networks and experience in building broader stakeholder portfolios. These findings suggest that inexperience may concentrate stakeholder engagement on customers, and that both AI tools and AI market hype can mediate pre-commitments in this context.

5.2.2 AI-Augmented Means in Product Development

Founders applied means-driven logic in product development by leveraging AI tools as expanded technical capabilities. AI coding assistants expanded technical execution capacity, enabling founders to conceptualize and build product possibilities within available means, as E5 described in 4.2. This effectively expanded their conception of *who I am* and *what I know* (Sarasvathy, 2001) to include AI-augmented coding capabilities for product development. Moreover, some founders also described using AI agents as decision consultation partners, seeking input on product prioritization while maintaining ultimate control. As E5 articulated in 4.2, they consulted "*Gemini agents who has like the context of pretty much everything about our company (...)*" while E14 characterized their agentic system as a person in the decision-making process (4.2). However, founders emphasized maintaining control, as E4 underlined in (4.2). This AI consultation usage may function as a compensatory mechanism for limited domain expertise in product development decisions (eg. McKelvie et al., 2011), providing an additional input source beyond customers.

Chandler et al.'s (2011) experimentation dimension of effectuation, where entrepreneurs try out different approaches through market-based trial-and-error, was clearly present in our cases and was supported by AI tools (e.g., E6 in section 4.3.1). The rapid prototyping capabilities of AI and the resulting increase in product iteration speed (E12, E17 in section 4.5) substantially reduced the financial cost of experimentation and experiential learning in product development. Prior research shows that effectuation can be learned through experiential trial-and-error or vicarious observation (Dew et al., 2009a; Minniti & Bygrave, 2001; Holcomb et al., 2009), but that such learning is often difficult because it is costly (Chandler & Hanks, 1998) and constrained by bounded attention, memory, and time (March, 1994; Simon, 1991). One plausible contributing factor to the strong presence of effectual logic in our sample is that AI tools lower these barriers by making trial-and-error and observation cheaper and faster, although we cannot rule out other explanations.

Several mechanisms may explain why less experienced founders demonstrated effectual logic in product development. AI tools may compensate for technical inexperience through coding assistance, while reduced experimentation costs may accelerate learning through rapid iteration cycles. Moreover, Frese et al. (2020) found that entrepreneurs with traditional *managerial* experience favour causation. In our case, the pool of interviewees is professionally inexperienced in general, which could also explain the lower use of causal logic. Beyond technological mechanisms, psychological factors may play a role. Engel et al. (2014) showed that entrepreneurial self-efficacy can enable novices to use expert decision logics under uncertainty. AI tools may enhance self-efficacy by providing tangible evidence of capability through rapid building and iteration. This suggests both technological and psychological mechanisms may operate together to enable effectual logic among less experienced AI founders, potentially lowering experience thresholds for effectual decision-making in technology-intensive domains.

5.3 Heightened Isotropic Uncertainty, Expanded Possibilities and Control Through Purpose Constraint

The use of effectuation under conditions of uncertainty has broad empirical support (Jiang & Tornikoski, 2019; Reymen et al., 2015; McMullen & Shepherd, 2006), with prior research on software contexts finding that perceived uncertainty drives experimentation and reduces causal logic (Frese et al., 2020). However, the AI startup context presented theoretically unclear predictions about how uncertainty would manifest and affect product development decision logic. Multiple forces operate simultaneously making future product market states increasingly difficult to predict and intensifying state uncertainty, one of them being AI as a general-purpose technology which evolves at an accelerating pace (United Nations, 2025; Yee et al., 2025; Ramoglou et al., 2025; Townsend and Hunt, 2019). The aggregate effect on founders' perceived uncertainty in product development decisions and resulting decision logic was theoretically ambiguous prior to empirical examination.

5.3.1 Sources and Experience of Isotropic Uncertainty in Product Development

Founders described experiencing heightened isotropic uncertainty in product development decisions from two primary sources, the AI field's characteristics and AI tools' capabilities. E6 described in 4.2 the abundance of "unexplored combinations" within the AI field for product possibilities. This expansion appears to reflect a clear manifestation of isotropic uncertainty, situations with too many product possibilities rather than too little information (Sarasvathy, 2009). This uncertainty was amplified by extreme developmental shifts affecting the product's feasibility, where E12 described in 4.5 being "*guided by technological shifts*", while E13 expressed in 4.5 excitement about new model releases that could fundamentally alter product capabilities. Rapid technological evolution (United Nations, 2025; Yee et al., 2025), means founders make product development decisions in environments where the competitive and technological landscape can shift dramatically with each capability release. Notably, this uncertainty appeared to energize rather than paralyze founders in product development, suggesting that contingency logic is strong.

AI tools themselves expanded feasible product opportunity space by enabling faster building (E4 in 4.5), effectively broadening the product decision space. E13 articulated in 4.2 the challenge of adaptability in product development when future technology direction is unclear. AI tools thus appear to operate with dual effects in product development, where they increase options and developmental velocity while simultaneously enabling faster product prototyping, which is further seen in previous literature (Ramoglou et al.,2025; Townsend and Hunt, 2019; Peng et al., 2023; Dell'Acqua et al., 2023; Batista et al., 2024). However, founders in our sample did not describe using AI for predictive uncertainty reduction in product development decision-making processes, as argued for in (Kim, 2025; Raneri et al., 2023; Lupp, 2023), instead focusing on AI as development acceleration tool, also explaining the increase in perceived aggregate uncertainty.

5.3.2 Effectual Logic Application Under Product Development Uncertainty

Heightened uncertainty in product development appears associated with extensive effectual logic application across all four principles in our sample, though causal direction cannot be established. This pattern broadly aligns with prior literature suggesting entrepreneurs adopt effectuation under high perceived uncertainty (Jiang & Tornikoski, 2019; McKelvie et al., 2011; McMullen & Shepherd, 2006). Moreover, means-driven logic (Sarasvathy, 2001) appears in our study to be particularly precent in product development contexts of expanded possibilities and limited predictability. When product futures are unpredictable and possibilities vast, commencing with available technical means may become more viable than attempting comprehensive predictive product planning, as founders emphasized action over extensive analysis in product development (E6 in 4.2, E13 in 4.2).

McKelvie et al. (2011) distinguish between state uncertainty (i.e. external environment) and effect uncertainty (i.e. action consequences), demonstrating that entrepreneurs act despite high state uncertainty but become reluctant when unable to predict their own action outcomes. Founders in our sample appeared to demonstrate willingness to make product development decisions despite substantial state uncertainty, brought by the AI landscape and its rapid technological evolution, evidenced by their proactive contingency orientation and means-driven product logic (sections 4.2 and 4.5). AI tools enabling rapid product prototyping may potentially reduce effect uncertainty in product decisions by allowing founders to observe product feature consequences quickly rather than committing to product directions with delayed feedback and thus reduce reluctance for action.

Furthermore, founders employed strategic limitation by minimizing team sizes (E6, E1 in 4.3.2), which reduced product decision space to cognitively manageable levels, maintaining control amid expanded product possibilities. Moreover, their customer commitments (E14 in 4.4) constrained the expanded product decision space created by AI tools and field possibilities, providing directional focus for product development amid overwhelming feature options. Additionally, founders did not merely respond to unexpected product market events but actively anticipated and sought technological change affecting product capabilities, as E12 described in 4.5 regarding monitoring technological shifts and maintaining product development flexibility. This proactive stance treats uncertainty as opportunity for product innovation rather than threat, aligning with Sarasvathy's (2001) contingency principle. However, this heightened uncertainty and required flexibility in product development also created tensions, with founders emphasizing speed's competitive importance and associated stress (E4 in 4.5), and time pressure as the biggest constraint in product decisions (E11 in 4.3.1), also highlighting the negative psychological effects of this applying this logic.

These finding contributes to understanding uncertainty manifestation in AI entrepreneurship product development contexts by suggesting that AI tools and the development of the AI market may generate new uncertainty forms. This AI effect on uncertainty can also be seen in previous literature (United Nations, 2025; Yee et al., 2025; Ramoglou et al.,2025; Townsend & Hunt, 2019). However, no interviewee said they used AI for predictive purposes, which was previously suggested in literature, and theorized to decrease effectual logic and increase causal logic (Kim, 2025; Lupp, 2023; Raneri et al, 2023). Moreover, the relationship between uncertainty and effectual logic in product development observed in our sample appears broadly consistent with prior research (McKelvie et al., 2011; McMullen & Shepherd, 2006; Sarasvathy, 2001; Frese et al., 2020), though the specific manifestation differs, including the heightened isotropic uncertainty from product possibility expansion, coupled with strategic constraint mechanisms and customer pre-commitment focusing. Thereby, this study contributes to the contextual understanding of how AI tools and the rapidly shifting AI market interplay with uncertainty and effectuation.

5.4 Summary of Analysis and Discussion

Our analysis reveals that effectuation persists in product development decision-making despite substantially changed antecedent conditions, manifesting through adapted forms shaped by contextual interaction. Control emerges as the unifying logic, in line with Sarasvathy (2001). Strategic constraint, customer co-creation, and temporal affordable loss reasoning each functioned as control mechanisms, also aligning with Sarasvathy's (2001,

2024) view that that effectuation minimizes the need for predictive information by emphasizing control.

Firstly, our findings suggest that the three transformed antecedents do not operate independently but interact to shape product development decision logic. Resource abundance interacts with uncertainty by expanding the feasible product opportunity space. Moreover, when financial constraints ease, and AI tools expand buildable scope, this creates isotropic uncertainty from possibility overload (Sarasvathy, 2009). Founders respond through strategic constraint mechanisms, suggesting that constraint functions as an uncertainty management mechanism when abundance creates decision complexity, indirectly applying Sarasvathy's (2001) *Pilot-in-the-Plane* principle.

Secondly, limited experience interacts with AI tools to enable capabilities that might otherwise require accumulated expertise. AI coding assistants expand technical means, while rapid prototyping enables earlier customer engagement that may compensate for insufficient domain knowledge. However, inexperience also intensifies reliance on customer co-creation, creating a reinforcing cycle where founders learn through co-creation rather than accumulating independent expertise. This may create an adapted pathway to effectual product development that differs from traditional expert-driven effectuation (Sarasvathy, 2001; Dew et al., 2009a).

Lastly, heightened uncertainty interacts with AI tools in a dual manner. AI tools expand product possibility space and accelerate technological evolution, intensifying state uncertainty (McKelvie et al., 2011), simultaneously, they may reduce effect uncertainty through rapid prototyping enabling quick validation. This dual effect may create favourable conditions for effectual logic, where founders can act despite environmental unpredictability because they can quickly observe product outcomes lowering effect uncertainty. This differs from traditional high-uncertainty contexts where both state and effect uncertainty remained high (McKelvie et al., 2011).

6. Conclusion

This study examined how AI-based software startup founders apply effectual decision-making logic in product development decisions, a context where traditional effectuation antecedents - resource scarcity, experience, and uncertainty - appear significantly transformed, through the following research question.

How do AI-based startup founders apply effectual decision-making logic in product development decisions, and how do AI development tools influence these decision processes?

Founders apply all five effectual principles through three key adaptations shaped by AI tools and contextual conditions. First, affordable-loss logic shifts from mainly financial to temporal currency, as capital abundance, AI-reduced experimentation costs, and market speed makes time the scarcest resource. Second, AI tools lower experience thresholds for effectual decision-making by augmenting founders' means and enabling rapid trial-and-error learning through prototyping. Third, AI tools transform uncertainty structure, heightening isotropic uncertainty from expanded possibilities, while reducing effect uncertainty through development acceleration. Across all findings, control emerges as the unifying logic (Sarasvathy, 2001, 2008), with founders actively constructing constraints through scope limitation and transforming contingency from reactive to proactive orientation. In summary, AI tools function as amplifiers rather than substitutes for effectual reasoning, enabling founders to apply control-oriented logic.

6.1 Theoretical Contribution

This study offers three main contributions to effectuation theory and AI-enabled entrepreneurship research. First, we demonstrate that effectuation persists across all five principles despite the transformed antecedents, with some instances of causal logic. Traditional effectuation research links the logic to resource scarcity, expertise, and uncertainty (Sarasvathy, 2001; Frese et al., 2020, Fisher, 2012), while our findings reveal these antecedents operate differently in AI contexts where effectuation remains dominant. Affordable-loss logic shifted from financial constraint to mainly temporal constraint, contradicting Dew et al.'s (2009b) time ambiguity proposition. Moreover, AI tools reduced financial experimentation costs while market velocity intensified temporal constraints, shifting the affordable-loss calculus from money to time. Less experienced founders employed effectual logic through AI-augmented capabilities, where AI coding assistants expanded technical means available to novices, effectively augmenting *who I am* and *what I know* (Sarasvathy, 2001) to include AI-augmented capabilities, as well as potentially lowering experience thresholds for effectual decision-making by reducing experimentation costs and accelerating trial-and-error learning. AI tools transform uncertainty structure in ways that favor effectuation, leading to founders experiencing heightened isotropic uncertainty from expanded possibilities while benefiting from reduced effect uncertainty through rapid prototyping. Notably, founders used AI for development acceleration rather than predictive uncertainty reduction, reinforcing control-oriented logic.

Second, we reveal control as the unifying logic across principles. Founders applied Sarasvathy's (2001, 2008) Pilot-in-the-Plane principle by strategically constraining scope through team limitation, customer focusing, and temporal protection. This shows that constraints can be actively constructed rather than only externally imposed, reflecting abundance management rather than scarcity navigation. In summary, AI startup founders apply effectuation through mainly control-oriented logic that adapts to transformed antecedents, with AI tools amplifying rather than replacing effectual reasoning.

Third, we identify AI tools as enablers rather than substitutes for effectuation. Rather than driving prediction-oriented planning, AI tools reduced experimentation costs, expanded technical means, enabled earlier customer engagement, and facilitated proactive contingency.

6.2 Implications for Practitioners

While we do not claim effectuation is superior to causal logic or test for venture success, our findings offer insights for founders navigating AI-intensive contexts. Treating time, attention, and cognitive capacity as primary constraints can help structure decisions when capital is available but complexity is high. Furthermore, deliberately limiting team size or narrowing scope may support more flexible, adaptive action under conditions of abundance-generated uncertainty.

AI tools can facilitate effectual approaches, particularly for less experienced founders, through rapid prototyping enabling early customer co-creation, allowing founders to gather quick feedback and move forward based on immediate possibilities. Additionally, founders seeking to engage customers earlier or more intensively may leverage AI's rapid iteration capabilities to enable user involvement that traditional software contexts made difficult. For venture capitalists and support organizations, the study suggests that understanding how founders actually make decisions in AI contexts requires recognizing that constraints can be a strategic choice. For effectual based logic decisions, protecting founders' cognitive bandwidth and enabling focused experimentation may be as important as providing capital in high-complexity environments.

6.3 Limitations & Future Research

This study has several limitations that offer opportunities for future research. First, findings are based on 17 early-stage AI startup founders in a Swedish context. While qualitative research does not aim for statistical generalization (Bell et al., 2022), founders in other geographic contexts, industries, or venture stages may experience different constraints and uncertainty forms. Comparative research across contexts could examine whether temporal affordable-loss logic and intensive customer co-creation persist beyond AI-intensive domains. Second, the study relies on self-reported accounts, which may be influenced by retrospective bias (Koller et al., 2025). Future work could triangulate founder perspectives with real-time observations, decision logs, or product analytics to examine how feature prioritization unfolds in practice and how AI tools are integrated into daily workflows. Third, we do not measure performance outcomes or examine which specific AI tool types influence decision-making in which ways. Longitudinal research could explore whether adapted effectuation leads to different growth patterns, pivot dynamics, or failure modes compared to traditional software startups. Fourth, our sample consists of AI-based startups where AI tool adoption is seemingly widespread and central to operations. It remains unclear whether AI tools influence effectual logic similarly in non-AI contexts where adoption rates and integration levels may differ substantially. Future research should examine how AI tools affect decision-making logics across industries with varying levels of AI adoption to understand whether our findings reflect AI-specific dynamics or broader patterns. Finally, data was collected during 2025, a period of intense AI market interest and rapid technological evolution, which could lead to drastically different results than being presented in the near future. Whether these patterns persist as AI technology matures and market conditions normalize remains an open empirical question.

Taken together, this study shows that early-stage AI-based software startups represent a fundamentally new empirical context, one that changes but ultimately enables elements of effectuation theory. Yet many of the mechanisms uncovered here remain only partially understood, and the broader entrepreneurial literature has not fully caught up with the speed at which AI is transforming decision-making in startups. Further empirical and theoretical work is therefore needed to clarify how decision-making logics evolve when technological capabilities accelerate. By expanding research across contexts, methods, and AI tool types, scholars can build a better understanding of how entrepreneurs navigate an increasingly complex environment filled with possibilities, which is important for both academic progress as well as supporting the next generation of AI-driven ventures.

7. References

Allyn, B. (2025, November 23). *Here's why concerns about an AI bubble are bigger than ever*. NPR. http://npr.org/2025/11/23/nx-s1-5615410/ai-bubble-nvidia-openai-revenue-bust-data-centers

Alvarez, S. A., & Barney, J. B. (2005). How Do Entrepreneurs Organize Firms Under Conditions of Uncertainty? *Journal of Management*, *31*(5), 776–793. https://doi.org/10.1177/0149206305279486

Ansoff, I. H. (1965). *Corporate strategy*. Sidgwick & Jackson.

Arend, R. J., Sarooghi, H., & Burkemper, A. (2015). Effectuation As Ineffectual? Applying the 3E Theory-Assessment Framework to a Proposed New Theory of Entrepreneurship. *Academy of Management Review*, *40*(4), 630–651. https://doi.org/10.5465/amr.2014.0455

Aryadita, H., Sukoco, B. M., & Lyver, M. J. (2023). Founders and the success of start-ups: An integrative review. *Cogent Business & Management*, *10*(3). https://doi.org/10.1080/23311975.2023.2284451

Bajwa, S. S., Wang, X., Nguyen Duc, A., & Abrahamsson, P. (2016). "Failures" to be celebrated: an analysis of major pivots of software startups. *Empirical Software Engineering*, *22*(5), 2373–2408. https://doi.org/10.1007/s10664-016-9458-0

Baker, T., & Nelson, R. E. (2005). Creating Something from Nothing: Resource Construction through Entrepreneurial Bricolage. *Administrative Science Quarterly*, *50*(3), 329–366.

Baron, R. A. (2004). The cognitive perspective: a valuable tool for answering entrepreneurship's basic "why" questions. *Journal of Business Venturing*, *19*(2), 221–239. https://doi.org/10.1016/s0883-9026(03)00008-9

Batista, S. S., Branco, B., Castro, O., & Avelino, G. (2024). Code on Demand: A Comparative Analysis of the Efficiency Understandability and Self-Correction Capability of Copilot ChatGPT and Gemini. *Proceedings of the XXIII Brazilian Symposium on Software Quality*, 351–361. https://doi.org/10.1145/3701625.3701673

Bell, E., Bryman, A., & Harley, B. (2022). *Business Research Methods*. Oxford University Press.

Berends, H., Jelinek, M., Reymen, I., & Stultiëns, R. (2013). Product Innovation Processes in Small Firms: Combining Entrepreneurial Effectuation and Managerial Causation. *Journal of Product Innovation Management*, *31*(3), 616–635. https://doi.org/10.1111/jpim.12117

Berg, V., Birkeland, J., Nguyen-Duc, A., Pappas, I. O., & Jaccheri, L. (2018). Software startup engineering: A systematic mapping study. *Journal of Systems and Software*, *144*, 255–274. https://doi.org/10.1016/j.jss.2018.06.043

Birt, L., Scott, S., Cavers, D., Campbell, C., & Walter, F. (2016). Member Checking: A Tool to Enhance Trustworthiness or Merely a Nod to Validation? *Qualitative Health Research*, *26*(13), 1802–1811. https://doi.org/10.1177/1049732316654870

Brandom, R. (2025, November 10). *A better way of thinking about the AI bubble | TechCrunch*. TechCrunch. http://techcrunch.com/2025/11/10/a-better-way-of-thinking-about-the-ai-bubble/

Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brettel, M., Mauer, R., Engelen, A., & Küpper, D. (2012). Corporate effectuation: Entrepreneurial action and its impact on R&D project performance. *Journal of Business Venturing*, *27*(2), 167–184. https://doi.org/10.1016/j.jbusvent.2011.01.001

Chandler, G. N., DeTienne, D. R., McKelvie, A., & Mumford, T. V. (2011). Causation and effectuation processes: A validation study. *Journal of Business Venturing*, *26*(3), 375–390. https://doi.org/10.1016/j.jbusvent.2009.10.006

Chandler, G. N., & Hanks, S. H. (1998). An examination of the substitutability of founders human and financial capital in emerging business ventures. *Journal of Business Venturing*, *13*(5), 353–369. https://doi.org/10.1016/s0883-9026(97)00034-7

Chandy, R. K., & Tellis, G. J. (2000). The Incumbent's Curse? Incumbency, Size, and Radical Product Innovation. *Journal of Marketing*, *64*(3), 1–17. https://doi.org/10.1509/jmkg.64.3.1.18033

Chen, C. C., Greene, P. G., & Crick, A. (1998). Does entrepreneurial self-efficacy distinguish entrepreneurs from managers? *Journal of Business Venturing*, *13*(4), 295–316. https://doi.org/10.1016/s0883-9026(97)00029-3

Chui, M., Hall, B., Singla, A., Sukharevsky, A., & Yee, L. (2023, August). *The state of AI in 2023: Generative AI's breakout year*. McKinsey & Company. https://mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

Considine, M., & Kharpal, A. (2025, November 14). *"Vibe revenue": AI companies admit they're worried about a bubble*. CNBC. http://cnbc.com/2025/11/14/vibe-revenue-ai-companies-admit-theyre-worried-about-a-bubble.html

De Clercq, D., Fried, V. H., Lehtonen, O., & Sapienza, H. J. (2006). An Entrepreneur's Guide to the Venture Capital Galaxy. *Academy of Management Perspectives*, *20*(3), 90–112. https://doi.org/10.5465/amp.2006.21903483

Dealroom. (2024). *AI Europe report 2024: Startup and VC data in the AI arms race*.

Dell'Acqua, F., McFowland, E., Mollick, E., Lifshitz-Assaf, H., Kellogg, K. C., Rajendran, S., Krayer, L. J., Candelon, F., & Lakhani, K. R. (2023). Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. *Social Science Research Network*, *24-013*. https://doi.org/10.2139/ssrn.4573321

Dew, N., Read, S., Sarasvathy, S. D., & Wiltbank, R. (2009a). Effectual versus predictive logics in entrepreneurial decision-making: Differences between experts and novices. *Journal of Business Venturing*, *24*(4), 287–309. https://doi.org/10.1016/j.jbusvent.2008.02.002

Dew, N., Sarasathy, S., Read, S., & Wiltbank, R. (2009b). Affordable loss: behavioral economic aspects of the plunge decision. *Strategic Entrepreneurship Journal*, *3*(2), 105–126. https://doi.org/10.1002/sej.66

Dias, S. E. F., Sadao Iizuka, E., & Vilas Boas, E. P. (2019). Effectuation theoretical debate: systematic review and research agenda. *Innovation & Management Review*, *17*(1), 41–57. https://doi.org/10.1108/inmr-12-2018-0094

Edmondson, A. C., & Mcmanus, S. E. (2007). Methodological fit in management field research. *Academy of Management Review*, *32*(4), 1155–1179. https://doi.org/10.5465/AMR.2007.26586086

Engel, Y., Dimitrova, N. G., Khapova, S. N., & Elfring, T. (2014). Uncertain but able: Entrepreneurial self-efficacy and novices′ use of expert decision-logic under uncertainty. *Journal of Business Venturing Insights*, *1-2*, 12–17. https://doi.org/10.1016/j.jbvi.2014.09.002

Engel, Y., Kaandorp, M., & Elfring, T. (2017). Toward a dynamic process model of entrepreneurial networking under uncertainty. *Journal of Business Venturing*, *32*(1), 35–51. https://doi.org/10.1016/j.jbusvent.2016.10.001

European Union. (2016, April 27). *EUR-Lex - 32016R0679 - EN - EUR-Lex*. Eur-Lex.europa.eu. http://data.europa.eu/eli/reg/2016/679/oj

Fisher, G. (2012). Effectuation, Causation, and Bricolage: A Behavioral Comparison of Emerging Theories in Entrepreneurship Research. *Entrepreneurship Theory and Practice*, *36*(5), 1019–1051. https://doi.org/10.1111/j.1540-6520.2012.00537.x

Floridi, L. (2024). Why the AI Hype is Another Tech Bubble. *Philosophy & Technology*, *37*(4). https://doi.org/10.1007/s13347-024-00817-w

Forbes, D. P. (2005). Managerial determinants of decision speed in new ventures. *Strategic Management Journal*, *26*(4), 355–366. https://doi.org/10.1002/smj.451

Foss, N. J., Andersson, M., Henrekson, M., Jack, S., Stenkula, M., Thorburn, K., & Zander, I. (2023). Saras Sarasvathy: recipient of the 2022 Global Award for Entrepreneurship Research. *Small Business Economics*, *61*. https://doi.org/10.1007/s11187-023-00746-6

Founders House. (2025). Founders-House.com. https://founders-house.com

Frese, M., & Gielnik, M. M. (2023). The Psychology of Entrepreneurship: Action and Process. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*(1). https://doi.org/10.1146/annurev-orgpsych-120920-055646

Frese, T., Geiger, I., & Dost, F. (2020). An empirical investigation of determinants of effectual and causal decision logics in online and high-tech start-up firms. *Small Business Economics*, *54*(3), 641–664. https://doi.org/10.1007/s11187-019-00147-8

Galkina, T., Atkova, I., & Yang, M. (2022). From tensions to synergy: Causation and effectuation in the process of venture creation. *Strategic Entrepreneurship Journal*, *16*(3). https://doi.org/10.1002/sej.1413

Garfinkle, A. (2025, November 29). *AI startup valuations are doubling and tripling within months as back-to-back funding rounds fuel a stunning growth spurt*. Fortune. http://fortune.com/2025/11/29/ai-startup-valuations-are-doubling-and-tripling-within-months-as-back-to-back-funding-rounds-fuel-a-stunning-growth-spurt/

Gartner. (2023). *Gartner Says More Than 80% of Enterprises Will Have Used Generative AI APIs or Deployed Generative AI-Enabled Applications by 2026*. Gartner. http://gartner.com/en/newsroom/press-releases/2023-10-11-gartner-says-more-than-80-percent-of-enterprises-will-have-used-generative-ai-apis-or-deployed-generative-ai-enabled-applications-by-2026

Geertz, C. (1973). *The Interpretation of Cultures: Selected Essays*. Basic Books.

Giardino, C., Paternoster, N., Unterkalmsteiner, M., Gorschek, T., & Abrahamsson, P. (2016). Software Development in Startup Companies: The Greenfield Startup Model. *IEEE Transactions on Software Engineering*, *42*(6), 585–604. https://doi.org/10.1109/tse.2015.2509970

Goel, S., & Karri, R. (2006). Entrepreneurs, Effectual Logic, and Over-Trust. *Entrepreneurship Theory and Practice*, *30*(4), 477–493. https://doi.org/10.1111/j.1540-6520.2006.00131.x

Gofman, M., & Jin, Z. (2023). Artificial Intelligence, Education, and Entrepreneurship. *The Journal of Finance*, *LXXIX*(1). https://doi.org/10.1111/jofi.13302

González, M., Terzidis, O., Lütz, P., & Heblich, B. (2024). Critical Decisions at the Early Stage of start-ups: a Systematic Literature Review. *Journal of Innovation and Entrepreneurship*, *13*(1). https://doi.org/10.1186/s13731-024-00438-9

Grégoire, D. A., & Cherchem, N. (2019). A structured literature review and suggestions for future effectuation research. *Small Business Economics*, *54*(4), 621–639. https://doi.org/10.1007/s11187-019-00158-5

Harms, R., & Schiele, H. (2012). Antecedents and consequences of effectuation and causation in the international new venture creation process. *Journal of International Entrepreneurship*, *10*(2), 95–116. https://doi.org/10.1007/s10843-012-0089-2

Hitt, M. A., Keats, B. W., & DeMarie, S. M. (1998). Navigating in the new competitive landscape: Building strategic flexibility and competitive advantage in the 21st century. *Academy of Management Perspectives*, *12*(4), 22–42. https://doi.org/10.5465/ame.1998.1333922

Holcomb, T. R., Ireland, R. D., Holmes Jr., R. M., & Hitt, M. A. (2009). Architecture of Entrepreneurial Learning: Exploring the Link Among Heuristics, Knowledge, and Action. *Entrepreneurship Theory and Practice*, *33*(1), 167–192. https://doi.org/10.1111/j.1540-6520.2008.00285.x

Hu, K. (2023, February). *ChatGPT sets record for fastest-growing user base - analyst note*. Reuters. http://reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/

Hubner, S., Most, F., Wirtz, J., & Auer, C. (2021). Narratives in entrepreneurial ecosystems: drivers of effectuation versus causation. *Small Business Economics*, *59*. https://doi.org/10.1007/s11187-021-00531-3

Islam, F., & Clun, R. (2025, November 18). Google boss Sundar Pichai warns “no company immune” if AI bubble bursts. *BBC*. https://www.bbc.com/news/articles/cwy7vrd8k4eo

Jiang, Y., & Tornikoski, E. T. (2019). Perceived uncertainty and behavioral logic: Temporality and unanticipated consequences in the new venture creation process. *Journal of Business Venturing*, *34*(1), 23–40. https://doi.org/10.1016/j.jbusvent.2018.06.002

Karami, M., Wooliscroft, B., & McNeill, L. (2020). Effectuation and internationalisation: a review and agenda for future research. *Small Business Economics*, *55*(3). https://doi.org/10.1007/s11187-019-00183-4

Kemell, K., Nguyen-Duc, A., Suoranta, M., & Abrahamsson, P. (2023). StartCards — A method for early-stage software startups. *Information & Software Technology*, *160*, 107224–107224. https://doi.org/10.1016/j.infsof.2023.107224

Kemell, K.-K., Elonen, A., Suoranta, M., Nguyen-Duc, A., Garbajosa, J., Chanin, R., Melegati, J., Rafiq, U., Aldaeej, A., Assyne, N., Sales, A., Hyrynsalmi, S., Risku, J., Edison, H., & Abrahamsson, P. (2020). Business Model Canvas Should Pay More Attention to the Software Startup Team. *IEEE Xplore*, 342–345. https://doi.org/10.1109/SEAA51224.2020.00063

Kim, J. (2025). Modeling Generative AI and Social Entrepreneurial Searches: A Contextualized Optimal Stopping Approach. *Administrative Sciences*, *15*(8), 302–302. https://doi.org/10.3390/admsci15080302

Kitching, J., & Rouse, J. (2020). Contesting effectuation theory: Why it does not explain new venture creation. *International Small Business Journal: Researching Entrepreneurship*, *38*(6), 026624262090463. https://doi.org/10.1177/0266242620904638

Klenner, N. F., Gemser, G., & Karpen, I. O. (2022). Entrepreneurial ways of designing and designerly ways of entrepreneuring: Exploring the relationship between design thinking and effectuation theory. *Journal of Product Innovation Management*, *39*(1), 66–94. https://doi.org/10.1111/jpim.12587

Klotins, E., Unterkalmsteiner, M., Chatzipetrou, P., Gorschek, T., Prikladnicki, R., Tripathi, N., & Pompermaier, L. (2019). A progression model of software engineering goals, challenges, and practices in start-ups. *IEEE Transactions on Software Engineering*, *47*(3), 1–1. https://doi.org/10.1109/tse.2019.2900213

Knight, F. H. (1922). Risk, Uncertainty and Profit. *The Quarterly Journal of Economics*, *36*(4), 682.

Koller, S., Ahmetoglu, G., & Stephan, U. (2025). Measuring entrepreneurs' use of effectuation as heuristics: Development and validation of a situational judgment test (SJT) for effectuation. *Journal of Business Venturing*, *40*(6), 106538. https://doi.org/10.1016/j.jbusvent.2025.106538

Koller, S., Stephan, U., & Ahmetoglu, G. (2022). Ecological rationality and entrepreneurship: How entrepreneurs fit decision logics to decision content and structure. *Journal of Business Venturing*, *37*(4), 106221. https://doi.org/10.1016/j.jbusvent.2022.106221

Kost, D. (2025, November 12). *AI Companies Don't Have a Profitable Business Model. Does That Matter?* Harvard Business Review. http://hbr.org/2025/11/ai-companies-dont-have-a-profitable-business-model-does-that-matter

Li, Y., Ring, J. K., Jin, D., & Bajaba, S. (2025). Elevating entrepreneurship with generative artificial intelligence. *Journal of Innovation & Knowledge*, *10*(6), 100820. https://doi.org/10.1016/j.jik.2025.100820

Lincoln, Y., & Guba, E. (1985). *Naturalistic Inquiry*. Sage Publications.

Logue, D., & Grimes, M. (2022). Living Up to the Hype: How New Ventures Manage the Resource and Liability of Future-Oriented Visions within the Nascent Market of Impact Investing. *Academy of Management Journal*, *65*(3), 1055–1082. https://doi.org/10.5465/amj.2020.1583

Lupp, D. (2023). Effectuation, causation, and machine learning in co-creating entrepreneurial opportunities. *Journal of Business Venturing Insights*, *19*, e00355. https://doi.org/10.1016/j.jbvi.2022.e00355

March, J. G. (1994). *A primer decision making : how decisions happen*. Free Press.

March, J. G., & Olsen, J. P. (1975). The uncertainty of the past: Organizational learning under ambiguity. *European Journal of Political Research*, *3*(2), 147–171. https://doi.org/10.1111/j.1475-6765.1975.tb00521.x

Matalamäki, M. J. (2017). Effectuation, an emerging theory of entrepreneurship – towards a mature stage of the development. *Journal of Small Business and Enterprise Development*, *24*(4), 928–949.

McKelvie, A., Haynie, J. M., & Gustavsson, V. (2011). Unpacking the uncertainty construct: Implications for entrepreneurial action. *Journal of Business Venturing*, *26*(3), 273–292. https://doi.org/10.1016/j.jbusvent.2009.10.004

McMullen, J. S., & Shepherd, D. A. (2006). Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur. *Academy of Management Review*, *31*(1), 132–152. https://doi.org/10.5465/AMR.2006.19379628

Melegati, J., Goldman, A., Kon, F., & Wang, X. (2019). A model of requirements engineering in software startups. *Information and Software Technology*, *109*, 92–107. https://doi.org/10.1016/j.infsof.2019.02.001

Millward, H., & Lewis, A. (2005). Barriers to successful new product development within small manufacturing companies. *Journal of Small Business and Enterprise Development*, *12*(3), 379–394. https://doi.org/10.1108/14626000510612295

Minniti, M., & Bygrave, W. (2001). A Dynamic Model of Entrepreneurial Learning. *Entrepreneurship Theory and Practice*, *25*(3), 5–16. https://doi.org/10.1177/104225870102500301

Mitchell, R. K., Busenitz, L., Lant, T., McDougall, P. P., Morse, E. A., & Smith, J. B. (2002). Toward a Theory of Entrepreneurial Cognition: Rethinking the People Side of Entrepreneurship Research. *Entrepreneurship Theory and Practice*, *27*(2), 93–104. https://doi.org/10.1111/1540-8520.00001

Moultrie, J., Clarkson, P. J., & Probert, D. (2007). Development of a Design Audit Tool for SMEs. *Journal of Product Innovation Management*, *24*(4), 335–368. https://doi.org/10.1111/j.1540-5885.2007.00255.x

Nguyen-Duc, A., Kemell, K.-K., & Abrahamsson, P. (2021). The entrepreneurial logic of startup software development: A study of 40 software startups. *Empirical Software Engineering*, *26*(5). https://doi.org/10.1007/s10664-021-09987-z

Nielsen, S. L., & Lassen, A. H. (2011). Identity in entrepreneurship effectuation theory: a supplementary framework. *International Entrepreneurship and Management Journal*, *8*(3), 373–389. https://doi.org/10.1007/s11365-011-0180-5

Nuseibeh, B., & Easterbrook, S. (2000). Requirements engineering. *Proceedings of the Conference on the Future of Software Engineering - ICSE ’00*, 35–46. https://doi.org/10.1145/336512.336523

Obschonka, M., & Audretsch, D. B. (2019). Artificial intelligence and big data in entrepreneurship: a new era has begun. *Small Business Economics*, *55*(3). https://doi.org/10.1007/s11187-019-00202-4

Obschonka, M., Grégoire, D. A., Nikolaev, B., Ooms, F., Lévesque, M., Pollack, J. M., & Behrend, T. S. (2024). Artificial Intelligence and Entrepreneurship: A Call for Research to Prospect and Establish the Scholarly AI Frontiers. *Entrepreneurship Theory and Practice*, *49*(3). https://doi.org/10.1177/10422587241304676

Packard, M. D., Clark, B. B., & Klein, P. G. (2017). Uncertainty Types and Transitions in the Entrepreneurial Process. *Organization Science*, *28*(5), 840–856. https://doi.org/10.1287/orsc.2017.1143

Pantiuchina, J., Mondini, M., Khanna, D., Wang, X., & Abrahamsson, P. (2017). Are Software Startups Applying Agile Practices? The State of the Practice from a Large Survey. *Lecture Notes in Business Information Processing*, *283*, 167–183. https://doi.org/10.1007/978-3-319-57633-6_11

Park, H., Luo, Y., & Yang, Y. (2025). Cost-effectively leveraging digital capital to develop means for effectual decision-making. *Strategic Entrepreneurship Journal*, *1*(62). https://doi.org/10.1002/sej.1547

Paternoster, N., Giardino, C., Unterkalmsteiner, M., Gorschek, T., & Abrahamsson, P. (2014). Software development in startup companies: A systematic mapping study. *Information and Software Technology*, *56*(10), 1200–1218. https://doi.org/10.1016/j.infsof.2014.04.014

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). *The Impact of AI on Developer Productivity: Evidence from GitHub Copilot*. https://doi.org/10.48550/arxiv.2302.06590

Perry, J. T., Chandler, G. N., & Markova, G. (2012). Entrepreneurial Effectuation: A Review and Suggestions for Future Research. *Entrepreneurship Theory and Practice*, *36*(4), 837–861. https://doi.org/10.1111/j.1540-6520.2010.00435.x

Politis, D., Winborg, J., & Dahlstrand, Å. L. (2010). Exploring the resource logic of student entrepreneurs. *International Small Business Journal: Researching Entrepreneurship*, *30*(6), 659–683. https://doi.org/10.1177/0266242610383445

Porter, M. E. (1985). *Competitive Advantage : Creating and Sustaining : Superior Performance*. The Free Press.

Prashantham, S., Kumar, K., Bhagavatula, S., & Sarasvathy, S. D. (2018). Effectuation, network-building and internationalisation speed. *International Small Business Journal: Researching Entrepreneurship*, *37*(1), 3–21. https://doi.org/10.1177/0266242618796145

Rady, J., Townsend, D., Hunt, R., & Simpson, J. (2025). The expectations game: The contingent value of hype as a rhetorical strategy in resource mobilization processes among AI startups. *Journal of Business Venturing*, *40*(4), 106499–106499. https://doi.org/10.1016/j.jbusvent.2025.106499

Ralph, P. (2016). Software engineering process theory: A multi-method comparison of Sensemaking–Coevolution–Implementation Theory and Function–Behavior–Structure Theory. *Information and Software Technology*, *70*, 232–250. https://doi.org/10.1016/j.infsof.2015.06.010

Ramoglou, S., Chandra, Y., & Jin, Q. (2025). Opportunity Search in the Era of GenAI: Navigating Uncertainty in an Expanding Universe of Imaginable but Unknowable Futures. *Journal of Management Studies*. https://doi.org/10.1111/joms.70011

Raneri, S., Lecron, F., Hermans, J., & Fouss, F. (2023). Predictions through Lean startup? Harnessing AI-based predictions under uncertainty. *International Journal of Entrepreneurial Behavior & Research*, *29*(4). https://doi.org/10.1108/ijebr-07-2021-0566

Rapp, D. J. (2022). Predictive vs. non-predictive entrepreneurial strategies: What's the difference, anyway? *Review of Managerial Science*, *16*(7). https://doi.org/10.1007/s11846-022-00519-7

Rapp, D. J., & Leunbach, D. (2025). Too good to be true? Toward an exploration of the "Triple Ds" of effectuation. *Journal of Business Venturing Insights*, *24*, e00576. https://doi.org/10.1016/j.jbvi.2025.e00576

Read, S., Dew, N., Sarasvathy, S. D., Song, M., & Wiltbank, R. (2009a). Marketing under Uncertainty: The Logic of an Effectual Approach. *Journal of Marketing*, *73*(3), 1–18. https://doi.org/10.1509/jmkg.73.3.001

Read, S., Song, M., & Smit, W. (2009b). A meta-analytic review of effectuation and venture performance. *Journal of Business Venturing*, *24*(6), 573–587. https://doi.org/10.1016/j.jbusvent.2008.02.005

Reymen, I. M. M. J., Andries, P., Berends, H., Mauer, R., Stephan, U., & van Burg, E. (2015). Understanding Dynamics of Strategic Decision Making in Venture Creation: A Process Study of Effectuation and Causation. *Strategic Entrepreneurship Journal*, *9*(4), 351–379. https://doi.org/10.1002/sej.1201

Ries, E. (2011). *The Lean Startup*. Portfolio Penguin.

Robbins, J. (2025, January 9). *AI startups grabbed a third of global VC dollars in 2024*. PitchBook. https://pitchbook.com/news/articles/ai-startups-grabbed-a-third-of-global-vc-dollars-in-2024

Sarasvathy, S. (2009). Effectuation: Elements of Entrepreneurial Expertise. *Journal of Management Studies*, *45*(1). https://doi.org/10.4337/9781848440197

Sarasvathy, S. D. (2001). Causation and effectuation: toward a Theoretical Shift from Economic Inevitability to Entrepreneurial Contingency. *The Academy of Management Review*, *26*(2), 243–263. https://doi.org/10.2307/259121

Sarasvathy, S. D. (2024). Lean Hypotheses and Effectual Commitments: An Integrative Framework Delineating the Methods of Science and Entrepreneurship. *Journal of Management*, *50*(8). https://doi.org/10.1177/01492063241236445

Sarasvathy, S. D., Dew, N., Velamuri, S. R., & Venkataraman, S. (2003). Three Views of Entrepreneurial Opportunity. In *Handbook of Entrepreneurship Research*. International Handbook Series on Entrepreneurship, vol 1.

Sarasvathy, S., & Dew, N. (2008). Effectuation and Over-Trust: Debating Goel and Karri. *Entrepreneurship Theory and Practice*, *32*(4), 727–737. https://doi.org/10.1111/j.1540-6520.2008.00250.x

Scape. (2025). *AI-native CRM that captures all your conversations*. Scape. https://scape.app

Seaman, C., & Guo, Y. (2011). Measuring and Monitoring Technical Debt. *Advances in Computers*, *82*, 25–46. https://doi.org/10.1016/b978-0-12-385512-1.00002-5

Shepherd, D. A., Williams, T. A., & Patzelt, H. (2015). Thinking about Entrepreneurial Decision Making. *Journal of Management*, *41*(1), 11–46. https://doi.org/10.1177/0149206314541153

Simon, H. A. (1959). Theories of Decision Making in Economics and Behavioral Science. *The American Economic Review*, *49*(3), 253–283. JSTOR. https://doi.org/10.2307/1809901

Simon, H. A. (1991). Bounded Rationality and Organizational Learning. *Organization Science*, *2*(1), 125–134.

Smolka, K. M., Verheul, I., Burmeister–Lamp, K., & Heugens, P. P. M. A. R. (2018). Get it Together! Synergistic Effects of Causal and Effectual Decision–Making Logics on Venture Performance. *Entrepreneurship Theory and Practice*, *42*(4), 571–604. https://doi.org/10.1177/1042258718783429

Stanford HAI. (2025). *Artificial intelligence index report 2025*. https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf

State of European Tech 2025. (2025). Stateofeuropeantech.com. https://www.stateofeuropeantech.com/chapters/executive-summary#firepower-for-ambition

Stockholm School of Economics. (n.d.). *Stockholm School of Economics Executive Education Data Integrity Policy*. Retrieved December 6, 2025, from https://exedsse.se/wp-content/uploads/2018/11/sss-executive-education-data-integrity-policy.pdf

Timmermans, S., & Tavory, I. (2012). Theory Construction in Qualitative research: from Grounded Theory to Abductive Analysis. *Sociological Theory*, *30*(3), 167–186. https://doi.org/10.1177/0735275112457914

Todd, P. M., Gigerenzer, G., & ABC Research Group. (2012). *Ecological rationality : intelligence in the world*. Oxford University Press.

Townsend, D. M., & Hunt, R. A. (2019). Entrepreneurial action, creativity, & judgment in the age of artificial intelligence. *Journal of Business Venturing Insights*, *11*(11), e00126. https://doi.org/10.1016/j.jbvi.2019.e00126

Townsend, D. M., Hunt, R. A., McMullen, J. S., & Sarasvathy, S. D. (2018). Uncertainty, Knowledge Problems, and Entrepreneurial Action. *Academy of Management Annals*, *12*(2), 659–687. https://doi.org/10.5465/annals.2016.0109

Townsend, D. M., Hunt, R. A., Rady, J., Manocha, P., & Jin, J. hyeong . (2024). Are the Futures Computable? Knightian Uncertainty and Artificial Intelligence. *Academy of Management Review*, *50*(2). https://doi.org/10.5465/amr.2022.0237

United Nations. (2025). *Technology and Innovation Report 2025*. Stylus Publishing, LLC.

Unterkalmsteiner, M., Abrahamsson, P., Wang, X., Nguyen-Duc, A., Shah, S., Shahid Bajwa, S., Baltes, G., Conboy, K., Cullina, E., Dennehy, D., Edison, H., Fernandez-Sanchez, C., Garbajosa, J., Gorschek, T., Klotins, E., Hokkanen, L., Kon, F., Lunesu, I., Marchesi, M., & Morgan, L. (2016). Software Startups - A Research Agenda. *Informatica Software Engineering Journal*, *10*(1), 89–123. https://doi.org/10.5277/e-Inf160105

Vásquez, Ó., Sandulli, F. D., & Gallego, J. (2026). Technological agglomerations and the emergence of artificial intelligence start-up ecosystems in Europe. *Technology in Society*, *84*, 103092. https://doi.org/10.1016/j.techsoc.2025.103092

Wang, X., Edison, H., Bajwa, S. S., Giardino, C., & Abrahamsson, P. (2016). Key Challenges in Software Startups Across Life Cycle Stages. *Agile Processes, in Software Engineering, and Extreme Programming*, *251*, 169–182. https://doi.org/10.1007/978-3-319-33515-5_14

Weick, K. E. (1979). *The social psychology of organizing*. New York Mcgraw-Hill.

Weiss, G. (2025, August 7). *YC founders have never been younger or under more pressure, due to AI*. Business Insider. https://www.businessinsider.com/yc-founders-younger-under-more-pressure-beacause-ai-2025-8

Werhahn, D., Mauer, R., Flatten, T. C., & Brettel, M. (2015). Validating effectual orientation as strategic direction in the corporate context. *European Management Journal*, *33*(5), 305–313. https://doi.org/10.1016/j.emj.2015.03.002

Wiltbank, R., Dew, N., Read, S., & Sarasvathy, S. D. (2006). What to do next? The case for non-predictive strategy. *Strategic Management Journal*, *27*(10), 981–998. https://doi.org/10.1002/smj.555

Wiltbank, R., Read, S., Dew, N., & Sarasvathy, S. D. (2009). Prediction and control under uncertainty: Outcomes in angel investing. *Journal of Business Venturing*, *24*(2), 116–133. https://doi.org/10.1016/j.jbusvent.2007.11.004

WIPO. (2025). *Global Innovation Index 2025*. World Intellectual Property Organization.

Xiao, J., Zhao, J., & Wu, L. (2025). *The Leonis AI 100 - Leonis Capital*. Leoniscap.com. https://www.leoniscap.com/research/the-leonis-ai-100

Yee, L., Chui, M., Roberts, R., & Smit, S. (2025). *Technology Trends Outlook 2025*. McKinsey & Company. https://www.mckinsey.com/~/media/mckinsey/business%20functions/mckinsey%20digital/our%20insights/the%20top%20trends%20in%20tech%202025/mckinsey-technology-trends-outlook-2025.pdf?utm_source=chatgpt.com

8. Appendices

Appendix A: AI Usage Statement

All the ideas, arguments, and findings, were written by the two authors exclusively, and all content in the thesis is human reviewed, edited, and validated. However, Artificial Intelligence, particularly Large Language Models (LLM's) were used to aid and support in the writing in order to enhance the quality of the thesis, in accordance with SSE policy on AI usage. The AI-models used were OpenAI's *ChatGPT* (5.1 Auto), *Claude* (Sonnet 4.5), and *Strawberry* (i.e. an agentic browser, beta version 0.0.72), which were all used in the same way for the same purpose, with no clear distinction between them, except for certain times Claude was used to ensure less context by the AI. They were used in two distinct parts of the thesis, in two different ways; (1) Data collection and analysis, and (2) Writing of the thesis.

Data Collection and Analysis

It is important to note that no confidential data or full transcripts were pasted into any LLM model. However, after transcripts were anonymized, the manual coding (see method 3. Method) was conducted, LLM models were prompted two questions, with example prompts being;

1. *Are there any sections or quotes that point toward the effectual principles (or its counterpart); means-driven action, affordable loss, pre-commitment and control? Provide me with sections or quotes based on this transcript: [Insert transcript]*
2. *Based on the codes I have written in the GoogleSheet, which ones are the most ambiguous, or obvious long-shots?*

Number (1) was asked in order to validate that all important aspects from interviews were considered, in order to limit human-bias in the coding process. All the codes generated by AI were then double checked and manually found by the authors before getting copied into the Google sheet. Number (2) was done in order to mitigate any bias that possibly arose, no code was immediately omitted based on the output, but they were all discussed critically to assure that no code was stretched to be used in the findings section. Overall, it was used to mitigate biases and human errors, and improved the quality by providing the thesis with a third opinion that could be used for sparking discussions between the authors.

Writing of the Thesis

During the actual writing of the thesis the AI models were applied in various ways; (1) Checking for grammatical errors, (2) improving flow or structures of sentences, (3) as an 'examiner' to critique different sections, and (4) providing examples of initial structures of the thesis, with examples of those prompts being:

1. *Check for any grammatical errors in this part, highlight anything that is wrong, and provide suggestions for correction, make sure to not change and content but only fix grammar: "[Insert sentence]"*
2. *This sentence isn't very nice to read, restructure it to make it flow better, make sure not to change any content or add anything new: "[insert sentence]"*
3. *Based on the grading criteria* [that has been feed into the 'project'/'agent'], *what grading would this section get. Be super harsh. And suggest what we need to add or clarify or delete for it to get a better grade: "[Insert section]"*
4. *What key elements need to be included in the abstract of a qualitative master thesis in order to get the best grade. Suggest a structure.*
5. *What does this* [Input concept/section/sentence] *mean in the context of the article [insert name], here is the text: "[Input the copied text, either full text or relevant section]"*

The first (1) and second (2) prompts were used in order to ensure readability and proper academic language of the thesis, increasing the quality of the overall ease of reading and language used. Importantly, no implementation was adapted without authors reading, reviewing, iterating and comparing to the original input to ensure academic integrity. In terms of number (3), it was used as a feedback option, where the AI could spot certain parts that needed clarification, or where we forgot to include something. All suggestions were not implemented, but certain feedback, such as the initial unclarity of a cross-case analysis and thematic analysis were iterated to ensure the correct method was used. Number (4) was only used when the authors felt that no obvious structure was to be implemented, where AI helped with the ideation stage. However, the sections, and structure of those, were iterated multiple times, and then compared to peer-reviewed academic papers. Number (5) was mostly used when writing the literature review, where certain parts of relevant articles were not understood, therefore AI was applied to explain it with other words. The output was then compared to the article to check for accuracy.

We do acknowledge that AI can make mistakes, especially when ideating or suggesting certain parts (eg. quotes or codes). However, no output was implemented blindly, but all was reviewed by the authors to ensure academic integrity.

Appendix B: Final Interview Guide

0) Opening Consent

- We are researching how early stage founders of AI-based software startups make and experience feature prioritization decisions during product development? that is understanding how you think, feel, and experience, choosing to develop new features. There is no right and wrong
- Asking for consent to record, informing them about anonymization, their right to retract at any given point without a reason, and how the data will be used

1) Context Questions

1. How old are you? How long have you worked in the field, and what is your position in the startup?
2. Please shortly describe, what does your product do, who is it for, and what stage are you at (team size, funding, revenue/traction)?
3. How do you experience / think it's different building an GenAI-startup compared to other startups? What kind of constraints do you experience? And what is easier and harder for you compared to other startups? How (if any) do you use different tools when building.

2) Anchor Episode

Think of the last time you had to choose what to build next (or what to cut). walk me through it end-to-end, like a mini timeline: the trigger, options on the table, who was involved, what you did, why you did it, and what you decided.

Potential Probes:

- How do you balance adding new features versus improving existing ones?
- What signals kicked this off?
- What evidence or tests most influenced you?
- When did you feel most uncertain? what reduced that uncertainty?
- What trade-off did you debate the longest?
- Looking back now, what would change your mind ?

3) Emotions

During high-stakes product decisions, what emotions show up for you (e.g., excitement, stress, fear of missing out, attachment to a vision)? How do think they help or hinder your choices?

Probes:
- Any moment you over-pushed a feature due to passion/hype? how did you notice and course-correct?
- What do you feel before a launch? What do you do when anxiety spikes before a launch (routines, people you call, data you seek)? Why not? How do you cope?

4) Decision Logic
When you prioritize between features (or actions), how do you balance intuition vs analysis?

Probes:
- Do you have a go-to way of scoring/picking ideas/features (even if it's just in your head)?
- If your co-founder had to call out your blind spot in product calls, what would they say?
- What's your "good enough to ship" rule? what's your "kill/pivot" rule?

5) New product development process
What's your current New Product Development timeline; from idea → prototype → ship → iterate?

Probes:
- Where do new feature ideas come from (users, sales, engineering, founder vision)?

6) External Factors & Constraints
Which outside forces / external stakeholder most shape your decisions/prioritization today?

Probes:
- Users/customers (who, how many, what kind of feedback matters most)?
- Investors/mentors (when do you listen vs push back)?
- Competitors or hype cycles (how do you avoid feature-chasing)?
- Constraints (capital, talent, compute, partnerships) that most influence scope/timing?

7) Intentionality, Meaning & Criteria
What makes a feature worth building for you? If you had to write the top 3 criteria on a whiteboard, what would they be?

Probes:

- Tell me about a time you said no to a seemingly attractive feature. why was that the right call?

8) Closing

1. What have you changed in your prioritization approach in the past year? what would future-you advise current-you?
2. Anything we didn't ask that matters for how you decide? anyone else we should talk to?

Appendix C: Relevant Quotes & Coding Examples

Examples of Coding					
Quotes	Interviewee	First-order code	Second-order code	Third-order code	Connection to theory
“Timing and urgency is the key component that will help us win”	E9	The need to move fast with urgency in order to succeed	Speed as competitive moat	Speed	Perceptions of the AI space
“Keep in mind what customers know and are comfortable with using”	E14	Understanding what customers want and know	Prioritizing customers' needs	Customer collaboration	Pre-commitment
“AI coding tools for sure. Like, I mean, it's 100% like life-changing.”	E16	AI tools as the biggest change in building products in the AI age	AI tools as important tools for building	Excitement for AI technology as available means	Means-driven logic

Examples of General Perception of the AI-space: Speed, Uncertainty, Financial Resources			
Quotes	Interviewee	Third-order code	Connection to theory
There's a lot of software being ripped out at the moment and replaced with the new AI players. So you want to position yourself as an AI player.	E10	Change in market	Perceptions of the AI space
It affects a lot, primarily in terms of speed, because building a horizontal product, there are so many things that one can build and want to build. And previously, we wouldn't be able to build everything that we have built in such a short time, which would then mean our growth would be slower, our product would be worse, not as impressive. And the time from getting an idea of a feature to actually getting it into production is like 10X shorter in many cases than what it was when building companies before AI.	E6	Speed	Perceptions of the AI space
It's for sure overwhelming with all of the different possibilities and paths you can take. And at some point, to some degree, it is pretty hard to identify if an idea you have is actually good or not, because there are so many good potential pathways that you can choose	E6	Uncertainty	Perceptions of the AI space
I think it can definitely become overwhelming [when you can build much and fast with AI tools]. Like, at some point you still have to decide, like,	E6	Many opportunities	Perceptions of the AI space

'cause you most often get a lot of ideas that you want to do or you can do or that people want you to do.			
I would say most [VCs] that we talked with now gets quite excited… I mean, [raising capital] is probably quite special compared to any other time in history… I really think, like, the big difference is that more people are keen to giving money away.	E3	Raising capital/financial means	Perceptions of the AI space
Yes, I think its easier to raise capital. Where like, AI is kind of our big note when it comes to building something different within the industry that we're building in.	E5	Raising capital/financial means	Perceptions of the AI space
Yeah in this industry, money flows, and a lot. There are a lot of VCs around, they are sharks for sure most of the time, especially with young founders. I feel like its a trend right now to invest in these really young founders, and it's all about fomo…it's very San Francisco inspired.	E17	Raising capital/financial means	Perceptions of the AI space
It's very uncertain, I don't think anyone has ever seen anything like this, not even the dot com bomb or other revolutions, I feel like the speed of AI is unique, and crazy.	E13	Speed	Perceptions of the AI space
The whole startup, point of startup is like racing against time	E16	Speed	Perceptions of the AI space
Other Quotes			
Quotes	**Interviewee**	**Third-order code**	**Connection to theory**
As a founder, I think you need to rely more on intuition, actually. Because if you overanalyze, that's what you're gonna do. And then you're gonna end up with feature overload.	E6	Starting with available means	Means-driven logic
One thing that we often realize, since me and the co-founder are both technical, one of our strengths is that we can get out new features and functionalities fast. And since we're not the best at selling…we actually in the sales process with customers can very swiftly turn a customer's request into a working functionality, instead of maybe trying to get better sales arguments that could get around that problem that the customer is explaining.	E3	Starting with available means	Means-driven logic
I think it's more true than ever that having a small and nimble, very capable team is super important. Like that's the foundation for any startup, and has been for a long time, but I think it's more so true than ever, because the companies that will stand out and will actually achieve both operational excellence but also excel over time and achieve their goals will be the ones with the best teams…a team that, you know, is capable of taking on a problem and looking at it from different perspectives and angles.	E2	Starting with available means	Means-driven logic

It's not so much about the idea. If we're a good team and we can improve fast, I knew that at some point we're going to strike gold.	E2	Starting with available means	Means-driven logic
AI coding tools for sure. Like, I mean, it's 100% like life-changing.	E16	Excitement for AI technology as available means	Means-driven logic
In the very beginning, like three or four months ago, I think then it was only intuition, and that's where, where you have to be that little Steve Jobs, right? About, you know, showing the world what you see with this technology	E4	Starting with available means	Means-driven logic
I’ve been exploring voice agents. I think why I did that was just 'cause there's just an enormous amount of use cases for taking notes right now. It had nothing to do with market feedback by then. It was just like, okay, voice agents plus phones should be interesting...Um, so that was kind of from the technology, kind of, okay, this technology is now here, you have these real time voice APIs, what can you do with it?...So it was, yeah, first from a technological perspective and then like a market perspective	E10	Excitement for AI technology as available means	Means-driven logic
I think that I am a very customercentric entrepreneur. I don't go around and try to impose my vision over people who are experiencing specific problems…the way that the problem is solved is up to us….So the whole conviction of how we have designed our product and how we are surprising the customer and again and again with like very smart ways to think the solution to their problem that is entirely on us…and creating a really cool solution that is based on our uh minds and convictions.	E9	Starting with available means	Means-driven logic
There's so much to be done with like just me and my co-founders imagination because a lot of these things aren't often very available to the customers…Because there's kind of a mismatch of what the customer actually even expects it to be able to do towards what we know that, okay, this might be possible. Let's build this crazy function for it.	E14	Starting with available means	Means-driven logic
When you're a young founder, then your disadvantage is that you know very little. Your advantage is that you can run very fast and work hard. And you have to lean in to that, what you have advantages, and to run fast you have to be very low ego and, and take...and be able to be brutally honest on like the feedback you get from customers. I think we've been pretty good in doing that…. and then of course like AI tools that help us validate stuff fast.	E1	Starting with available means	Means-driven logic
For the first year of building the product, that [coolness, fun-ness, exploring] was the main motivator. It was a lot of passion. It was fun. It was interesting. It was exploring new grounds... That was so early as well. I think it was more excitement of exploring new features in the beginning.	E3	Excitement for AI technology as available means	Means-driven logic
We have Claude Code in for the backend. We have Playgo for the frontend... I mean, there's so many little tools, right? Like every, every database provider has AI these days.	E4	Excitement for AI technology as available means	Means-driven logic

We have prioritized exploring what's possible rather than making them perfect.	E3	Starting with available means	Means-driven logic
We all suck at design, so we ask Claude the, you know, 'What, what would you do?' Uh, because we have no clue	E4	Starting with available means	Means driven logic
We don't work on the vision yet. Like we have a very specific problem we are solving and we haven't solved it. When we solve that very specific problem then it's going to be a question of like where does the company go?...But then there's the feeling which is like of course being very different and like AI-first and like really creating a really really good product for these people. And I think that's not necessarily where the company is going, but how the company is doing it.	E9	Rejecting Conventional Planning Models	Means-driven logic
Let's say we have 80 hours per week to work. So then we have a list of things that needs to get done. And everyone has responsibility to get these done…we maybe spend 65 of the 80 hours on that. And then the rest of the hours, we have opened to potentially explore these other crazy features and ideas that everyone individually has. So we always leave a bit room to do that. [...] And this way of working is enabled by AI, being able to iterate so fast.	E6	Rethinking Product Development with AI	Means-driven logic
I would say the biggest difference is the fact that it's quite different how and what you can create in what timeframe today, compared to what was possible two and a half years ago, or a bit more. So the pace of creating new products and functionalities is significantly different, and that changes the playing field quite significantly.	E3	Rethinking Product Development with AI	Means-driven logic
I think it's very rewarding. You can go from idea to features superfast... It's super fun.	E3	Rethinking Product Development with AI	Means-driven logic
I mean, [AI coding tools] absolutely makes it much quicker. We can actually have others do stuff as well [not just technical staff] because it's actually not that hard. You don't have to do everything from scratch.	E8	Rethinking Product Development with AI	Means-driven logic
Everything just from the legal side…we always graph with some type of AI tool first in order to save money and save time. And then, of course, writing code, like that's a big part of what we do every day, and I think it will become even more integrated into many of the workflows that we... I mean, have, like, not just the engineers, but also ask, you know, people that work on go-to-market, that work on marketing, so on and so forth. So it's really widespread in that sense. I think it gives you that kind of operational upper hand. It gives you opportunities to spend that money elsewhere. -E2	E2	Rethinking Product Development with AI	Means-driven logic
So everything's easier today. You first and foremost have to kind of embrace where we stand today. Like if you're just thinking that, okay, I'll create another SAAS, I think you're heading in a direction where it will be hard to defend yourself and create dependability in your product over time because moats are rare these days. My belief is that if you want to start today, you're gonna have to build AI native for sure, and for me that's like really building	E2	Rethinking Product Development with AI	Means-driven logic

on the models even where they might be flawed today. Because I think you have to have an optimistic mindset that things will be improving			
I think it's, it's more fluent and flexible in the sense that more happens. Like, more unexpected things happen, right? If you have a new feature or idea… we can implement it in four or six hours."	E4	Rethinking Product Development with AI	Means-driven logic
If you're building an AI native company, if you're building a company that in any ways uses LLMs, if you're building a company that can be aided in the process of writing code by using LLMs and foundational models, you will experience an efficiency boost in doing so, compared to not doing so. I mean, there's a lot of studies on this. Stack Overflow's developer report from 2025, shows very clear numbers on that. Developers are using these tools and are pursuing efficiency gain. There's still a hesitancy to its accuracy, so therefore you have to use them with caution. So therefore, I think all companies in that category, which I think is an increasing amount in total, is experiencing that efficiency increase. But there are still companies that don't use AI and can have fantastic results regardless. And that is because building a great company stems from a thousand factors.And AI is only one of them, right? It's a tool, a means. Uh, it's not the solution to building a great company.	E12	Rethinking Product Development with AI	Means-driven logic
I think the main difference is just the pace you need to move at. Um, it's way higher. And now you can move at a way higher pace also. But yeah, I don't think it was possible to, uh, like, build products as fast in the past…probably five days faster than we would do, like, two years ago. At least if you're going for this, like, 80/20 approach just to test something out, and get feedback	E15	Rethinking Product Development with AI	Means-driven logic
Cursor is kind of like so 2023, maybe early 2024. Uh, but since cloud code came in, like it's… the go-to platform and they're using it heavily.	E16	Development with AI	Means-driven logic
But what I actually usually do is I give the agents a specification of the feature, and then I ask if there's any questions of the specification, is there anything unclear? Then they just go through the current state of the app and compare it with my specification and then ask for clarifications. That usually gives double the accuracy of the feature that the agent builds	E3	AI as a Collaborative Team Member	Means-driven
We record everything in Notion. I have my own kind of agents, so to speak, that I feed this into. Based on that, I ask the agent to then kind of bucket them into different categories to help me.	E2	AI as a Collaborative Team Member	Means-driven logic
I use AI a lot when I don’t know anything, it’s my best friend, it makes me solve problems much faster honestly.	E13	AI as a Collaborative Team Member	Means-driven logic
It doesn't necessarily always have to come from a problem, which is the traditional way of seeing it, because we're building such a high-tech solution. We sometimes come up with cool ideas, and solutions to a lot of different problems that is not maybe as specified	E6	Rejecting Conventional Planning Models	Means-driven logic

It's not always better to think more thoroughly about everything. It's not always good. Because if you overanalyze, that's what you're gonna do. And then you're gonna end up with feature overload	E6	Rejecting Conventional Planning Models	Means-driven logic
To be honest, sometimes you have to forget the long term things. At least now, that's the state we're now, like, does it help the customer now? Then f**k long term vision. (laughs) We'll fix it later.	E3	Rejecting Conventional Planning Models	Means-driven logic
We don't have any [framework] set in stone. I think we do have a kind of underlying ambition to be rooted in like concrete and like established facts…it's facts from like, okay, we know that our customers have said this. I mean, it's kind of a culture thing, right? We don't have anything written down.	E3	Rejecting Conventional Planning Models	Means-driven logic
I think it's more like currently like… test it out, let's see, let's scrap it. It's more like on a feeling basis	E8	Rejecting Conventional Planning Models	Means-driven logic
I don't think I have a good framework for it…like if we have clear feedback from users, then we just prioritize that…But mostly, I think it comes down to intuition	E5	Rejecting Conventional Planning Models	Means-driven logic
There is a pretty clear bias of your view of what you think the product will be in the future, which is a really, really strong vision that you have around the product. That can sometimes clash with what your users say and believe.	E6	Rejecting Conventional Planning Models	Means-driven logic
Those features or those parts of the product that you're building out has to have projected value towards the end goal that you're trying to achieve. If that's pulling you in a completely different direction, maybe that's the indication that you need to pivot. Maybe that's the indication that, you know, you're going about the problem the wrong way.	E2	Rejecting Conventional Planning Models	Means-driven logic
I think a lot of AI companies today, they don't really do the right things…they don't spend a lot of time on discovering the problem. They don't really build for their customers…they just build for everybody or like very very big things…the key is to be very very niche and really like understand your customers and build something that people want to pay for and then dream of changing an entire industry…but with AI it kind of changed like now everybody's like 'revolutionizing like customer success' and like all that, it's like too big.	E9	Rejecting Conventional Planning Models	Means-driven logic
It can be, like, a negative thing sometimes, overindulge on, on the vision. I think it was the wrong decision to try to constrain the vision from the get go.... from a market perspective.I think it's much better to just go out there and get the feedback of what people are doing with your product and then let the product evolve in that sense and if you find something that you're even more excited about then regarding the vision, then that's good instead of trying to constrain it-	E15	Rejecting Conventional Planning Models	Means-driven logic
I can build something and kill it, that's the best part, it goes so fast. The problem is that I am a perfectionist, so I kill a lot.	E17	Building and Scrapping Features	Affordable loss reasoning

Time. I think time is our biggest constraint, but I mean, it's a bad answer because everything boils down to time in life	E2	Temporal resource framing	Affordable loss reasoning
I know the cost of this approach but it still makes sense.	E16	Temporal resource framing	Affordable loss reasoning
Another thing is that we always encourage ourselves to build small things often. Like if we have an idea, we should do it. If we can do it in one or two days, we should just do it. But it's a very difficult feature to solve and it takes some time. So we had to think about if this is worth it or not because there's so many other things we want to build.	E6	Temporal resource framing	Affordable loss reasoning
One of the biggest [decision criteria for what to build] is time. How long does it take? And the other one is, how much value does it bring?	E3	Temporal resource framing	Affordable loss reasoning
People can build so fast, so are you able to build stuff that other people do not have time to build? If the climate as a whole moves quite fast, yeah then the fact that you're moving even faster is probably weighing a bit heavier in the AI space	E3	Temporal resource framing	Affordable loss reasoning
We talked a lot about how that makes quality suffer long term. Um, but whether or not is there's even an alternative because, if we did it the proper way someone else, especially in the super competitive market, would be just two weeks faster by taking the risk of maybe not building the most bulletproof product but being two weeks faster and thereby taking over any market	E4	Temporal resource framing	Affordable loss reasoning
The AI space in general moves very, very fast. We try to just like focus on building fast just on user feedback, we get and our own intuition and try to just like iterate on it. We got to plan it a bit just like make sure everything, is in place and then just like build as fast as possible. Time is everything.	E5	Temporal resource framing	Affordable loss reasoning
Obviously number one customer number two would be then how fast can we build it	E7	Temporal resource framing	Affordable loss reasoning
I think [the industry's] speed is ultimately good for us because it pushes our speed of execution. And then it makes you feel like you need to move faster, and makes your feedback loop faster	E6	Temporal resource framing	Affordable loss reasoning
Like even if we have these tools that can, do 20 things in parallel we can't process all of that. So that in combination with time pressure, puts a constraint on us that we can't, we can't do every idea we want to do. So, we just have to try and do what's most valuable	E11	Expanded Possibilities, Increased Decision Uncertainty	Affordable loss reasoning
and the tools are great for shipping fast so we can collaborate with customers and get their feedback, and emphasis on fast. At the end of the day, if everyone has tools like this, and AI is speeding up the development of AI, you just have to keep up. Especially as a small start-up. But because of these tools, and because it feels like there is a revolution in the market and AI	E13	Expanded Possibilities, Increased Decision Uncertainty	Affordable loss reasoning

startups could try and target every single vertical in the world. All of these opportunities make it difficult to make decisions, I think.			
I think that's one of the hardest thing, because as a startup, you need to keep focus. As soon as you lose focus, it's dangerous. Even though you might have a lot of money, it's all about then you have to attract the right talent.	E2	Purposeful team constraining	Affordable loss reasoning
there, it's much easier to, to like to build stuff. So, like, five or 10 years ago, you would just need to have more people to build, like, the same things that we're building, like, with this team now. So, so even if we would be as intentional as we are now in some features, it would maybe need like five people to execute on it in the same speed as we can do now with two. Um, so that is like a big difference.	E1	Purposeful team constraining	Affordable loss reasoning
I also think that's the trend inside AI network companies, just doing more with fewer people. If you're fewer people, it's way easier to align on, this is the most important thing, …and this is what we're gonna execute on. In the AI age you're, like, pushing code so fast. There's changes all the time. And when you're more people, that information flow just goes a lot slower and you need to build up a lot of structures surrounding it.	E15	Purposeful team constraining	Affordable loss reasoning
At times I want to have a lot of manpower, but I think that would be the death of us. Because where are we even heading, you know? It's better to really be sure in these early stages, and then its better to be fewer in my opinion. And we don't even need to be that many I think…we're productive.	E17	Purposeful team constraining	Affordable loss reasoning
When you have the feature idea and we have the feature specifications, you can almost instantly get 80% of the work done. Now, I can just take that specification of the feature that you would have done anyways before, but you can just send it into the coding engine. It writes out maybe an outline of that feature.		AI-Amplified Individual Productivity	Affordable loss reasoning
we are still using co-pilot and trying to see how much we can do with as little coding and this little little effort because we want to make sure that clients actually need this. Um but we've used co-pilot then and that's primarily just as you're coding you can give it tasks to do give it small tasks to do so you don't need to sit there and code the whole thing.	E7	AI-Amplified Individual Productivity	Affordable loss reasoning
And the bigger team is not necessarily good because the product will get more dispersed. You will lose control. You will lose focus on the core.	E6	AI-Amplified Individual Productivity	Affordable loss reasoning
I think that's one of the hardest thing, because as a startup, you need to keep focus. As soon as you lose focus, it's dangerous. Even though you might have a lot of money, it's all about then you have to attract the right talent.	E2	AI-Amplified Individual Productivity	Affordable loss reasoning
I also think that's, like, that's the trend inside AI network companies, just doing more with fewer people. I mean, you really have to prioritize what you think is the absolute necessity- to build, but I almost think that's a good thing, because otherwise you end up spending a lot of time building stuff that maybe wasn't, like, super essential	E15	Purposeful team constraining	Affordable loss reasoning

I think how we're going about it is that every time we have a [user] case or so, that's kind of where we improve the product.	E8	Customer collaboration	Pre-commitment
What I feel usually is doing right by the customer. It is my motive usually. I feel a responsibility to be a representative for them. Like I was selected as their chancellor or their spokesperson on their behalf. I always want to represent their needs.	E2	Customer collaboration	Pre-commitment
Like user feedback, uh, of course we have, uh, like channels when it comes to that, like users can just like write their feedback straightaway, uh, into our web app. Um, they also are very- very engaged, uh, on Instagram, like, DM'ing us, uh, about things that they think should be improved.	E5	Customer collaboration	Pre-commitment
we're building if the customers ask for it and then the customers they ask for a specific big stuff and then um my job is to understand what it is that key feature that they would need in order to trust us that we can build everything else around it -	E9	Customer collaboration	
I think when you're sitting so close to users and you're listening to their narrative and their experience for a close on, you get a quite strong, um, conviction on where you should build and what you should build, and when you're further away from that, your last reference point of what users are actually saying about your product is dead way before you start building	E12	Customer collaboration	Pre-commitment
Apart from making the team stay focused in the world of opportunities, the only truth we can rely on is our customers. Who knows what the world is going to look like in five, even a year. We can't control the future of AI, or maybe a little (laughing)...but we can be the, you know, absolute best at listening to our customers and you know bridging that with all the cool technology available to us, and lastly just have a f**king cracked team of devs	E13	Customer collaboration	Pre-commitment
We're in an industry that we're we haven't been in before. So to say um because that's the thing we we right now don't build anything until we confirm it with a customer and that's just because we aren't in the industry and that might be a good thing because then we're not building things that our customers don't need -E7	E7	Customer collaboration	Pre-commitment
The people that I trust the most…the kind of feedback I value the highest…is the ones that actually are paying us, because that means they have skin in the game. That means that they actually come with something out of a need themselves. Because everyone can give you advice, or everyone can give feedback and say that, 'Hey, I really want this,' and then they end up not paying for it.	E2	Self-selected customers as important	Pre-commitment
I mean, it's the customer that affects what we're building because they are going to be the ones that pay us. They are going to be the ones that give us ideas, connections, uh, and everything.	E9	Self-selected customers as important	Pre-commitment

Everybody wants to be nice. Everybody says, "Yeah, that's cool." …but if people are not like genuinely excited about something…that means just that they don't care enough. So it's mainly talking with customers and actually diving deep to see if they're just being nice or if they are actually, like, genuinely excited.	E1	Self-selected customers as important	Pre-commitment
The [number] one criteria [for if a feature is worth building] is if users talked about it at all. Has it been mentioned by users?	E6	Customer collaboration	Pre-commitment
[A decision criteria for developing a feature] is if it makes the experience nicer for the customer or the end user.		Customer collaboration	Pre-commitment
I think mostly it's, it's talking to, to customers, right?	E14	Customer collaboration	Pre-commitment
I think for us it's just back to the client. It's always back to the client	E7	Customer collaboration	Pre-commitment
One thing that we do is actually in the sales process with customers, we can very swiftly turn a customer's feature request into a working functionality. By getting the idea, you're getting the feature done within one or two days, and then getting it to test with customers within three to five days.	E3	Rapid Prototyping with Early Customers	Pre-commitment
And the first demo of this product is done in Lovable actually.	E8	Rapid Prototyping with Early Customers	Pre-commitment
I think product development is way faster because you test more, and in the end, any early stage startup is about implementing a feature as fast as possible and then crashing with reality and then reiterating.	E4	Rapid Prototyping with Early Customers	Pre-commitment
For us it's like we had to to generate like a specific specific um like not drawing but like an image or like an illustration of the products that we are working with and I think generally in the past you know you would spend a lot of time to create that but now if you are actually like solving problems with AI first then you can actually have an MVP and show that you can do it for for the customer much faster	E9	Rapid Prototyping with Early Customers	Pre-commitment
The faster you can get a client testing something, the faster you can iterate. So that's extremely important. Best case scenario, they're like testing something from day one	E7	Rapid Prototyping with Early Customers	Pre-commitment
We were getting this feeling of there's a problem we can solve from this customer who really needed something, and that kinda sparked an idea, "Oh, we could build it in this way.". We used Cloud Code, had it build something, and then we plugged it in, tried it out in a test environment, and then we could record a video and show that, and basically that was our proof of concept.	E11	Rapid Prototyping with Early Customers	
[The hype around AI] is just, in a good way, I would say that it pushes everyone's boundaries. And more of a general feeling that anything is possible, that people are more optimistic about certain features. And there's a	E6	Leveraging AI Hype	Pre-commitment

general view of pushing the boundaries of technology, which allows you to try out more things and experiment more. And it's positive intellectually because everyone starts thinking more about the future and what technology can do. And then that way when you discuss it more together, everyone hype it up together, you come up with these revolutionary ideas			
The only moat we have compared to bigger companies is that we can move super fast.We can work really close to our customers	E3	Leveraging AI Hype	Pre-commitment
I mean, one concrete thing is that I can work on two totally separate features on our platform at the same time. So I could have two agents in GitHub Co-pilot, which I've done today, one of them works on for example our email verification functionalities, as well as having one working on functionalities of generating tests, for example	E3	AI-Enabled Parallel Building and Low Switching Costs	Contingency Logic
Our priorities in building our core features are still the same and come from the team, but we're open to smaller spontaneous features depending on trends and other releases.	E6	Shifting Priorities in a Fast-Moving AI Landscape	Contingency Logic
You, you kind of wanna, at some level, stay with the, the general public's kind of knowledge of how, how the system works and what they can do, uh, while still kind of eyeing forward of like, "Okay, what's happening? What are the, like, model providers saying? What's, uh, research saying?" Uh, like building for that but optimizing it for the current, current state essentially	E14	Shifting Priorities in a Fast-Moving AI Landscape	Contingency Logic
I think it's very different [building in the AI space], especially in the way that GenAI is so new that things change every day. And we meet so many people building things with GenAI. And a lot of people do AI verticals, for example. And everyone is just trying to take the newest, latest tool, build something with that. I think the biggest challenge with it is to just be on top of everything new that comes every single day.	E11	Shifting Priorities in a Fast-Moving AI Landscape	Contingency Logic
I think it's super personal. I think it's very rewarding. You can go from idea to features superfast. I think it's very rewarding. It's super fun.	E3	Embracing Rapid Change as Opportunity	Contingency Logic
I would think I would regret if I don't build something, because there's so much opportunities.	E16	Embracing Rapid Change as Opportunity	Contingency Logic
One element is this sense of time pressure, right? When all of Twitter talk about [AI development] every day, then you feel like, we have to move faster, f**k the little things, let's do something new.	E4	Embracing Rapid Change as Opportunity	Contingency Logic
I think for me [what makes a feature worth building] is about the novelty of what we're building. There is one aspect of what we're building that is going to be truly novel to the world, and what's happening in this field makes that exciting.	E12	Embracing Rapid Change as Opportunity	Contingency Logic

And if anything, I think like that leaves so many opportunities that it is changing so much. And like no one knows the entire truth of, of like how to build these things effectively essentially.	E14	Embracing Rapid Change as Opportunity	Contingency Logic
My belief is that if you want to start today, you're gonna have to build AI native for sure, and for me that's like really building on these new models even where they, where they might be flawed today. Um, because I think you have to be with an optimistic mindset that things will be improving	E2	Embracing Rapid Change as Opportunity	Contingency Logic
So, even though it hurts a bit to remove it, I think we will.	E3	Pressure of building fast	Negative effects
There's a lot of pressure also because you need to get that out fast.	E3	Reluctance to "kill" feature	
I would say definitely I'm reluctant to, to killing things.	E14	Reluctance to "kill" feature	Negative effects
Like, it can be really good in a way that you're every day trying to figure out a solution to every problem you have, like trying to find your way out of a bad situation. But at the same time, it can also be bad in the way that you might make the wrong decision because you have that time pressure on you. We think it's a good idea, but we tried to go wide, but it felt like we don't have enough time to actually, like, validate this with everyone. So, that's made us pivot…I think it's definitely something in the AI space because things happen so quickly there compared to if you just go into legacy industries and do something there with or without AI. Maybe I'm in a space where, everyone's trying to find a new revolutionary idea that grows to a billion-dollar company. So that's maybe slightly different in the way that it's more stress-inducing	E11	Pressure of building fast	Negative effects
We need this high growth curve and if not, we're leaving, we're leaving it behind.	E10	Maximizing expected returns	Casual logic
It's really exciting because it's a very strategic thinking. It's a lot of creativity that's needed because you're thinking into the future and trying to envision how the future of technology will look like.So it's, it's pushing the limits of your brain basically. So it's exciting, it's challenging, of course but I think we all love challenges. So we get excited by that challenge. You find that sometimes users show you how the future will be, and sometimes users don't know how the future will be. And you kind of have to predict what's gonna happen, and short-term, users might not understand but long-term, it's gonna work.	E6	Trying to predict the future	Casual logic
I think technology trends is more interesting because that's like, how can you ride the next wave in trying to predict where things are heading. Even though like most cases you will be wrong anyways.	E2	Trying to predict the future	Casual logic

Appendix D: Examples of Reflexive Notes

Example 1:

- *Before*: expect super clear processes and decision logics, considering how they behave in daily life
- *During*: Talked a lot about values and vulnerable moments in their life, probably because they felt safe with us
- *After*: Make sure not to apply any of my emotional values from knowing them from before, and not applying the "character development" into any data - it's not relevant to the study. Probably should have made sure they stayed a bit more on topic, but it is hard to do when they get super vulnerable about certain points
- *Surprise*: Surprised by how thought through their personal values were and how vulnerable they are. They did talk about how that has shaped them as a person. Considering I know them and I know that they are very structured and has preferred processes, I thought they would have clearer processes of how to make decisions.

Example 2:

- *Before*: I expect that they are very nice and maybe not that opinionated
- *During*: Very hard to understand. A lot of words and thoughts but they aren't very connected.
- *After*: They said a lot of things without a lot of reading. Possibly there could be answers to questions in random places in the interview. Questions might have been too broad as they kept asking for specific examples. It is important that if the next interviewee does the same that we actually narrow the questions down a bit.
- *Surprise*: They expressed way more opinions than I thought they would, and some of them are a bit on the controversial side, and since I know who he has worked with before I know where they stem from and how they evolved. Make sure however to not include anything about that relationship in the data.

Example 3:

- *Before*: I think she is very knowledgeable in her field, and they have done great things with their company. I am excited to see how she approaches these questions.

- *During*: When she talks about the emotional side of things, she really opens up more detailed after about how she thinks about decision making. Talks about things that have happened today or thing week in regards to product and features -> this is good!
- *After*: I feel like the most interesting part we come back to are the decision making aspects of things, and how AI tools interact with this, and how they feel overwhelmed about all the options that they are facing. It feels like after we have talked about emotional stuff, the interviewees seem to open up more about decision making, almost like it makes them feel more comfortable to be honest. Maybe it primes them to think deeper about things, and that it is okay to be honest - not giving "the right answer". At this point, I think this is what we should continue looking into.
- *Surprise*: I think I was expecting more structure and rigid planning and models for making these decisions. I also thought that maybe when she mentioned AI tools that she was going to say that they use it for prediction or testing the market, which wasn't necessarily the case. Think we should not be biased and think that AI tools -> less uncertainty going forward.

Example 4:

- *Before*: This is someone that I know professionally so, I will try and not be biased and open minded. I will try and make sure he knows there are no right or wrong answers, so that he will answer as freely as possible and not try to please me.
- *During*: Professional answers, very honest. No real structured approach to decision making, I think.
- *After*: I think sitting in the interview I felt like there was no structure to the decision making process, but I think it was more about that there were not many formal decision making structures, and that there was little planning. Now when I've read more theory, I really feel like this looks like effectual decision-logics, not just random answers. And reflecting on the last interview, the logics are very alike.
- *Surprise*: The thing about having money + having a smaller team is more common than I though, I could already see it was a trend in the industry from our experience, but I'm surprised how much they have reflected on the reasons and made the choice so strategically.